Intrapersonal and Interpersonal Dynamics In Personality Expression

A Complex Dynamical, Enactive, and Embodied Account

NICOL ALEJANDRA ARELLANO VÉLIZ

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The research of this thesis was conducted at the research unit Developmental Psychology of the Heymans Institute for Psychological Research at the Faculty of Behavioural and Social Sciences, University of Groningen, the Netherlands.

The PhD project was accomplished with financial support from Agencia Nacional para el Desarrollo y la Investigación (ANID), Chile. Programa Becas Chile (Scholarship 72200122).

Cover design & digital art

Nicol Arellano Véliz - The artwork for this thesis was created by the author using Adobe Firefly, based on an original photograph taken at Allardsoog, The Netherlands.

Layout

Initial layout draft by Rocío Hernández - Design, revisions and final layout by Nicol Arellano V., inspired by Lisette de Jonge-Hoekstra.

Printing

Ridderprint - www.ridderprint.nl

Intrapersonal and Interpersonal Dynamics in Personality Expression: A Complex Dynamical, Enactive, and Embodied Account.

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PhD thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. J.M.A. Scherpen
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

Thursday 12 December 2024 at 12.45 hours

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Table of Contents

"Life and mind share a core set of formal or organizational properties, and the formal or organizational properties distinctive of mind are an enriched version of those fundamental to life. More precisely, the self-organizing features of mind are an enriched version of the self-organizing features of life."

Evan Thompson
(2010)

Chapter 1

General Introduction

There is a fundamental coupling between individuals as embodied agents and the environments within which they are situated –which are also constituted by other individuals (Varela et al., 1991; Johnson, 2015; Di Paolo, 2021; Nowak et al., 2020). Such an environment presents opportunities for action where the agent and environment are coupled through cycles of mutual interactions that are reciprocal but not necessarily symmetrical, also known as reciprocal causality (Thompson & Varela, 2001) or circular causality (e.g., Fuchs, 2020). We are connected to our immediate environments through the organic constitution of our bodies. In this sense, psychological science must encompass dimensions such as embodiment, the immediate environmental context, and intersubjectivity to understand the mind comprehensively (Thompson, 2007).

Within this rich and interconnected landscape, personality theory fits, offering a framework for understanding how individuals behave, interact, appraise, and ultimately shape their worlds. Personality is crucial for understanding the interactions between individuals and their environments, and it is a vital ingredient in this individual-environment interaction when viewed through the lens of complex, dynamic, enactive, and embodied perspectives. Thus, personality is not merely a static trait confined to the individual; it is a dynamic component of the broader system that extends beyond the individual. Therefore, the patterns and stylistic differences constituting personality are integral components of the complex adaptive systems that characterize human beings. This reflection should point out that the traditional way of measuring personality (traditionally with self-report questionnaires) and its expression may have to incorporate this dynamic perspective, capturing personality's fluid and adaptive qualities as it manifests through embodied interactions and dynamic engagements with the world.

This thesis explores the study of individuals' embodied dynamics connected to psychological traits, in particular, adults' personality expression in individual and interpersonal dynamics through body motion and speech synchronization. In the last chapter, the study of infants' temperament and limb motion dynamics extends this connection between embodied dynamics and psychological traits. All chapters incorporate an integrative complex dynamic, enactive, and embodied perspective as will be introduced below.

Enactive, Embodied, and Complex Systems Approaches in the Psychological Literature: Concepts covered in this thesis

This thesis employs interrelated theoretical frameworks: ***enactive, embodied, and complex dynamical systems approaches***. These complementary frameworks describe the dynamic, reciprocal relationship between individuals and their environments. ***Enactive*** theory describes how agents shape their experiences through ongoing interactions with their surroundings, emerging a complex adaptive individual-environment system (Thompson & Varela, 2001; Thompson, 2007). Here ***embodiment*** is a fundamental element because an ***embodied mind*** reflects and integrates the current state of the whole organism as it enacts the environment (Varela et al., 1991; Gallagher, 2018; Fuchs, 2020). The embodied mind is not separate but rather an integral bodily subject whose experience extends throughout the ***whole body*** engaging directly with the world (Thompson, 2007; Chemero, 2009; Baggs & Chemero, 2021; Fuchs, 2020). Therefore, the body is not merely a receptacle but the very core of the subject, where perception, sensation, consciousness, and action emerge (James, 1890; Merleau-Ponty, 1945/2013; Fuchs, 2020).

Embodied cognitive scientists view individuals as dynamical systems where variables change continuously and interdependently over time according to dynamical laws (Chemero, 2009). The ***complex dynamical systems (CDS)*** framework offers a methodological toolbox to study nonlinear dynamics and embodied interactions within a complex adaptive system, leading to emergent properties and behavioral patterns (Thompson & Varela, 2001; Richardson & Chemero, 2014). This approach is dynamic because it examines how system behaviors evolve over time (Kelso, 1995; Richardson & Chemero, 2014), bridging the agent-environment boundary crucial for understanding cognitive systems (Chemero, 2009). Complex systems are generally understood hierarchically, so the different levels that constitute them can range from molecules, intra-individual processes (e.g., physiological functioning, personality traits), individuals, and dyadic systems (interpersonal interactions), to groups, or societies (Nowak et al., 2020).

We can extend these insights to the study of ***personality traits***, laying the groundwork for exploring how personality is expressed in actual behavior through the individual's bodily engagement and contextual interactions (e.g., Richardson et al., 2014). The enactive approach proposes that the patterns that constitute behavior, and in this case, personality, influence and emerge from the interaction between an individual and their environment in a reciprocal causality form (e.g., Thompson & Varela, 2001; Hovhannisyan & Vervaeke, 2022; Satchell et al., 2021). The embodied approach emphasizes the importance of the body's role in shaping experience and behavior, suggesting that personality traits are deeply intertwined with our physical makeup and movements (e.g., Koppensteiner, 2011; Jiang et al., 2023). The complex systems approach allows us to study personality as part of a dynamic system, where multiple interacting components give rise to emergent properties that cannot be fully understood by examining each component in isolation (e.g., Fajkowska, 2015; Nowak et al., 2020; Michaels et al., 2021). However, the relationship between system-level dynamics and individual personality traits can be indirect and more complex. There may be mediating factors (e.g., situational constraints), feedback loops (e.g., within dyadic interactions), and non-linear interactions that affect how emergent patterns from a complex system translate into distinct personality features over time and situations. In this sense, we can say that the complex emergent patterns of behavior, affect, cognition, and desire (Wilt & Revelle, 2019) would constitute the stylistic differences that characterize distinct personality traits or dimensions.

Complex systems are interconnected and inseparable from their environments, aligning closely with the principles of enaction and embodiment (Gallagher & Appenzeller, 1999). In psychology, this translates into studying dynamic patterns of thought, affect, and behavior over time and situations (Nowak & Vallacher, 1998; Nowak et al., 2002, 2005; Richardson, Dale & Marsh, 2014). Complex systems exhibit several fundamental properties, that can differ in the way that are presented by different authors; however, they refer to the same foundations. First, complex systems are composed of ***interacting components*** (Richardson & Chemero, 2014); therefore, they are subject to ***interaction-dominant dynamics*** which indicate that behavior results from interactions among system components and environmental factors (Anderson et al., 2012). ***Emergence*** refers to new structures and patterns that arise through self-organization, exemplified by coherent behaviors that cannot be predicted from individual components (Goldstein, 1999; Van Dijk, 2021). ***Self-organization*** refers to behavioral patterns emerging without a centralized controller, evident in natural phenomena like walking or birds flocking, and in human synchronization (Yun et al., 2012; Richardson et al., 2014). ***Soft-assembly*** indicates that behavior emerges from the temporary coalition of components, indicating individual-environment coupling dynamics (Kloos & Van Orden, 2009). ***Nonlinearity*** is a fundamental property and indicates that behaviors are not directly proportional to inputs, leading to unexpected outcomes (Van Orden et al., 2003). ***Iterativity, iterative causality, or recursiveness*** describes how the current state of a system impacts the next, creating feedback loops that can be self-stabilizing or self-amplifying (Van Geert, 1998; Van Dijk, 2021).

Furthermore, complex systems can display complex and unpredictable behavior, also referred to as ***chaos***, even when governed by simple rules. This chaotic behavior arises from the sensitive dependence on initial conditions, where small differences can become amplified over time, making long-term predictions impossible (Richardson et al., 2014). This principle challenges the notion of randomness in behavioral events, suggesting that seemingly random behavior may not be truly random (Guastello & Liebovitch, 2009; Den Hartigh et al., 2017).

In line with the enactive, embodied, and CDS frameworks described, a phenomenon that underlies all these perspectives and occurs in natural systems is ***synchronization***, which is studied throughout this thesis. Synchronization is a fundamental mechanism for understanding human functioning, including how interpersonal and intra-individual dynamics emerge and it helps explain the dynamics of the interacting components that constitute complex systems (e.g., Vallacher et al., 2002; Nowak et al., 2020). People naturally synchronize their behavior in response to environmental and intra-individual factors (Nowak et al., 2020). This model explains how coherent functional units emerge from the synchronization of lower-level elements in the brain, mind, and social systems, enabling information integration and the emergence of functions (Nowak et al., 2017, 2020). In the field of personality, it helps us to study how interpersonal and intra-individual dynamics emerge (e.g., Nowak et al., 2020; Michaels et al., 2021). For example, we can explore how interpersonal synchronization differs between dyadic systems that are composed of individuals with very similar or dissimilar personality traits; or, how intra-individual synchronization varies in individuals with certain personality traits profiles. In the context of this thesis, I specifically focused on the synchronization of body motion and speech linked to personality traits.

Synchronization helps us to understand the process by which the dynamic patterns that characterize personality emerge from the coupling of lower-level elements. It further allows us to see how different ***affordances*** (i.e., opportunities for action perceived in the environment; Gibson, 1980) align and promote an optimal grip with the world, facilitating smoother interactions and more adaptive behaviors. It is relevant to mention that the relationship between synchronization and personality is thought to be bidirectional and to occur as a process governed by circular causality (e.g., Fuchs, 2020; Nowak et al., 2020), meaning that synchronization can influence the expression of the patterns that constitute personality traits across situations; and can promote the emergence of novel properties in dyadic interactions (Nowak et al., 2020). And, vice versa, the way individuals synchronize in dyadic interactions can be understood as the interaction of their "personality systems" which will lead to novel emergent properties (e.g., weaker/stronger interpersonal synchronization) that are partly explained by the elements that constitute the personality of both interacting systems (Shoda et al., 2002; Nowak et al., 2020). More on this theme will be elaborated in-depth throughout the different chapters of this dissertation. This comprehensive approach helps us realize the fluid and adaptive qualities of personality, particularly, by its manifestation through embodied dynamics at intra-individual and interpersonal levels, the engagements with the world, and the functional synchronization underpinning these processes. The central research questions guiding this dissertation can be phrased as***: How do dynamic bodily and speech patterns reflect the interplay between personality traits, temperament, interpersonal synchronization, and environmental interactions?***

This dissertation

Chapter 2 provides a foundational framework for achieving the comprehensive approach described above. The chapter integrates enactive, embodied, and complex systems perspectives into personality science, emphasizing the interconnectedness of organisms and the environment. This elaborates on the connection between personality and the theory of relevant affordances within the individual-environment coupling. The following three empirical chapters explore adult personality expression, interpersonal, and intra-individual synchronization through body motion (Chapters 3 and 4) and speech synchronization (Chapter 5). Chapter 6 extends the previous approaches to infants, examining the relationship between motor system organization, temperament, and maternal anxiety at 6 and 12 months of age. Chapters 3 and 4 are published in peer-reviewed journals, Chapters 5-6 are submitted and published in the form of preprints, and Chapter 2 is a manuscript in preparation.

Chapter 2: Integrative Perspectives on Enactive, Embodied, and Complex Systems Applied to Personality Science

This chapter provides a theoretical foundation, comprising the main topics of this thesis and some beyond its scope. Personality traits are defined as individual differences in behavior patterns, affect, cognition, and desire that emerge in the engagement with the environment in which individuals are situated (e.g., Wilt & Revelle, 2019; Satchell et al., 2021). Personality is further conceived as a dynamic construct closely connected with the engagement with relevant affordances, reflecting tendencies to optimally grip the world (e.g., Hovhannisyan & Vervaeke, 2022), for which the enactive and complex dynamical systems perspectives offer a meaningful framework.

The chapter begins by integrating enactive, embodied, and complex dynamic systems theories into a unified perspective. It explores how complex dynamical systems theory contributes to the study of personality by examining dynamics at different levels, including intra-individual and interpersonal levels. The concept of functional synchronization is introduced across these levels. The chapter advocates for a comprehensive framework encompassing various dimensions such as ***embodied, dynamic, self-organizing,*** and ***intersubjective*** aspects. It also incorporates the ***skilled intentionality framework***, rooted in the field of relevant affordances (Rietveld et al., 2018), suggesting that personality traits influence an individual’s engagement with environmental affordances and sensorimotor processes.

Chapter 3: The interacting partner as the immediate environment: Personality and interpersonal dynamics

In social interactions, humans tend to voluntarily and involuntarily synchronize their body motion, which expresses many individual differences and can impact interaction appraisals. Building on part of the foundation elaborated in the previous section, Chapter 3 transitions from theory to experimental research. It particularly focuses on the role of ***personality traits Extraversion and Agreeableness*** (social traits) in the emergence of ***interpersonal synchronization and dynamic organization of body motion in dyadic interactions***. For this aim, young adults followed a conversation with three topics: 1) introduction, 2) self-disclosure, and 3) argumentative. Post-interaction appraisals were explored in the form of interpersonal closeness, affect, and enjoyment as a way of intersubjective outcomes. Regarding the techniques employed, body motion was assessed using *Motion Energy Analysis* (MEA; Ramseyer, 2020), a frame-by-frame differentiation method. Interpersonal bodily synchronization was estimated as (a) synchronization strength using ***Windowed Lagged Cross-Correlations*** and (b) Dynamic Organization (Determinism, Entropy, Laminarity, Mean Line) using *Cross-Recurrence Quantification Analysis* (see Table 1).

Chapter 4: Personality expression in body motion dynamics: An enactive, embodied and complex systems perspective

Following the theme of the previous chapter, to explore ***personality expression in body motion dynamics*** but at the ***intra-individual level***, in Chapter 4, we explore the connection between body motion dynamics and personality differences (Big Five dimensions). For this, young adults completed a 15-minute task covering three self-referencing topics: 1) introduction, 2) bodily perception and sensory life, and 3) socio-emotional life. Body motion dynamics were extracted from video recordings using the same frame-by-frame differentiation method previously introduced, *Motion Energy Analysis* (MEA, Ramseyer, 2020). In this case, ***Recurrence Quantification Analysis (RQA)*** was employed to operationalize self-organizing dynamics expressed in motion dynamics through the variables of Determinism (deterministic patterns), Entropy (complexity), Laminarity (laminar states), and Mean Line (stability) (see Table 1). Affect state was included to evaluate how the participants appraised and experienced the task. Multilevel models estimated personality (Big Five domains/dimensions) and situational effects.

Chapter 5: Beyond Words: Speech Synchronization and Conversation Dynamics Linked to Personality and Appraisals

This chapter explores the role of ***personality*** in ***speech synchronization*** during dyadic conversations among young adults. In particular, it was studied how personality differences and conversation topics predict interpersonal speech synchronization, leading/following dynamics, and nonverbal interactional dominance in dyadic conversations. The experimental task is the same as presented in Chapter 3, where participants had a 15-minute conversation following the three topics (introduction/ self-disclosure/argumentation) in our laboratory. In this case, the focus was studying their speech synchronization and turn-taking (speech/silence) dynamics were assessed through nonlinear time-series analyses: ***Categorical Cross-Recurrence Quantification Analysis (CRQA), Diagonal Cross-Recurrence Profiles (DCRP),*** and ***Anisotropic-CRQA*** (see Table 1). From the time series, we extracted five variables to operationalize speech synchronization (global and at lag-zero), leading-following dynamics, and asymmetries in the interacting partners' nonverbal interactional dominance. Interaction appraisals were explored in high detail using a perception of the interaction questionnaire (Cuperman & Ickes, 2009). Associations between personality traits Extraversion/Agreeableness, speech synchronization, and nonverbal interactional dominance were tested using mixed-effects models.

Chapter 6: Relationship between temperamental dimensions and infant limb movement complexity and dynamic stability

This final empirical chapter examines the relationship between ***motor system complexity, stability, and temperamental traits at 6 and 12 months of age***. The reasoning of this chapter is that infant temperament dimensions describe behavioral responses to stimulation, while motor systems undergo considerable changes during infancy and are influenced by caregivers' mental health. In this study, we investigate how temperamental traits are associated with high-level measures of motor system organization at 6 and 12 months across three different types of play. To capture the effects of caregiver mental health, we also include maternal trait anxiety in our analyses. The longitudinal sample consists of 83 infants at 6 months and 59 infants at 12 months. Limb movements were measured with wearable accelerometers during three tasks involving their caregiver: book sharing, manipulative toys, and rattle-shaking. Using ***Multidimensional Recurrence Quantification Analysis (MdRQA)***, we extracted the variables of Entropy and Mean Line to provide information on the system's complexity and stability, respectively (see Table 1). Using mixed-effects models, we evaluated the predictive effects of task and temperamental variables—Negative Emotionality (NEG), Positive Affectivity or Surgency (PAS), and Orienting and Regulatory Capacity (ORC). The data for this study was collected at the Baby Lab of the Polish Academy of Sciences by collaborator and co-author Zuzanna Laudańska.

Chapter 7: General Discussion

This chapter presents a general discussion that summarizes and integrates the findings from all studies, addressing their implications and suggesting future research directions. I discuss how this dissertation has elucidated significant connections between personality traits and dynamic patterns in both body motion and speech synchronization. Moreover, this approach has been effectively extended to infants, revealing links between temperament dimensions and motor limb organization—specifically motor complexity and stability. It is discussed how the embodied and dynamic patterns may reflect and constitute what we label as personality, laying the ground for future empirical research. Additionally, some future directions and relevant methodological insights are discussed, particularly regarding the optimal use of time series analysis, elements to keep in mind when interpreting dynamic measures, and how their use can be improved in future studies.

Overall, this dissertation advances our understanding of personality by emphasizing the central role of embodied dynamics. It offers a compelling argument for viewing personality traits as emergent phenomena arising from the complex interplay between individuals and their environments, as well as embracing the emergent properties that arise from the interaction between different "personality systems". This advocates for an enactive, embodied, and complex dynamical approach that paves the path for future research that further explores these phenomena and underlying mechanisms.

Table 1. Summary of the techniques and variables included in this thesis

Measure	Purpose in Study	Description	Variables
Windowed Lagged Cross-Correlations (WLCC)	Chapter 3: To quantify temporal dependencies and interactions between body motion time series in dyadic interactions.	A linear statistical technique measuring lagged correlations between two time-series using a sliding window (Schoenherr et al., 2019).	Strength of interpersonal synchronization (Fisher's Z grand average, Ramseyer, 2020).
Cross Recurrence Quantification Analysis (CRQA)	Chapter 3: To quantify synchronized behaviors and mutual influences between interacting individuals through body motion.	A nonlinear time series technique extends recurrence analysis to two time-series from the same or different systems (Wallot & Leonardi, 2018).	Determinism, Entropy, Laminarity, Mean Line.
Recurrence Quantification Analysis (RQA)	Chapter 4: To quantify dynamic organization (self-organizing dynamics) of body motion at the individual level.	A nonlinear time series analysis technique that measures the recurrence of states in a system's reconstructed phase space (Marwan et al., 2007)	Determinism, Entropy, Laminarity, Mean Line.
Categorical Cross-Recurrence Quantification Analysis (Categorical CRQA)	Chapter 5: To quantify synchronized behaviors and mutual influences between interacting individuals in speech turns.	Similar to CRQA, but for categorical time series, speech synchronization is assessed (Cox et al., 2016).	Global Recurrence Rate, RR_{global} (all lags); Recurrence rate across the line of synchrony, RR_{LOS} (lag zero).
Diagonal Cross-Recurrence Profiles (DCRP)	Chapter 5: To quantify conversational imbalances and leading-following dynamics in interactions.	Analyzes the recurrence of behaviors at various time lags along the main diagonal (Line of Synchrony) in cross-recurrence plots (Dale et al., 2011).	Quotient of the DCRP (Q_{DCRP}) as an index of leading-following dynamics.
Anisotropic CRQA (aCRQA)	Chapter 5: To quantify each partner's influence and asymmetry in nonverbal interactional dominance.	Identifies horizontally or vertically oriented structures in cross-recurrence plots for categorical time series (Cox et al., 2016; Xu et al., 2020).	Relative difference in Laminarity (LAM_{ARD}) and Trapping Time (TT_{ARD}) to quantify the extent and duration of asymmetries.

Table 1. Summary of the techniques and variables included in this thesis (continued)

Measure	Purpose in Study	Description	Variables
Multidimensional Recurrence Quantification Analysis (MdRQA)	Chapter 6: To quantify motor (limbs) system organization in a multidimensional system.	Analyzes multiple layers of data over time by integrating multiple recorded time series into a single phase space (Wallot et al., 2016; Hall et al., 2023).	Entropy, Mean Line.

Chapter 2

Integrative Perspectives on Enactive, Embodied, and Complex Systems Applied to Personality Science

To be submitted as:

Arellano-Véliz, Nicol A., Kunnen, E. Saskia, Castillo, Ramón D. & Cox, Ralf, F.A. Integrative Perspectives on Enactive, Embodied, and Complex Systems Applied to Personality Science.

Abstract

Enactive, embodied, and complex dynamical systems approaches have convergences in the field of psychological science, employing a comprehensive framework for studying personality and individual differences. This paper explores the dynamic interplay between individuals with their environment, emphasizing the emergence of temporal patterns and dynamics across social, individual, and material dimensions. Personality is conceptualized as a dynamic process influenced by enactive engagement with relevant affordances, reflecting tendencies to optimally navigate the world, using enactive and complex dynamical systems perspectives. The enactive approach, incorporating embodied principles and nonlinear dynamic systems methods, offers a unified perspective on behavioral, cognitive, affective, and social processes. Complex dynamical systems tools enhance the understanding of personality by examining the interplay of constraints, such as organismic and environmental factors. The paper advocates for a broader framework encompassing embodied, dynamic, self-organizing, soft-assembled, synergetic, and intersubjective dimensions. We further incorporate the skilled intentionality framework, grounded in the perspective of affordances, which suggests that personality traits contribute to an individual's skills and drive sensemaking in continuous engagement with environmental affordances that are perceived differently depending on individual differences, in this case, personality.

Keywords: enactive approach, embodied cognition, complex dynamical systems, personality dynamics, affordances, self-organization, temporal patterns, nonlinear dynamics, skilled intentionality, individual differences

1. Introduction

Enactive and embodied approaches are becoming increasingly more prominent in psychological science. In alignment with these conceptual perspectives, the application of complex dynamical systems methods provides a wide landscape of theoretical, methodological, and practical tools. In the present work, we aim to integrate enactive, embodied, and complex systems theories toward the study of personality. By doing so, we understand personality as the dynamic interplay between the organic and agentic constitutions of human bodies and the environment in which they are situated. This interplay implicates the emergence of temporal patterns and dynamics through the engagement with the social, individual (e.g., self-organization and sensemaking), and material world. Even though these processes are highly context-sensitive (e.g., environmental constraints) or soft-assembled, and dynamic (changing over time), it is possible to observe global regularities and individual differences in behavior, affect, and cognition.

This chapter begins by presenting the fundamentals of enactive, embodied, and complex dynamical systems theories. It then introduces the concept of functional synchronization in human functioning, applying these theories to the study of personality traits. The Skilled Intentionality Framework (SIF, Rietveld et al., 2018) is discussed to explain how individuals engage with multiple affordances and the role of personality traits in promoting embodied readiness for these engagements. The chapter concludes with an exemplification through a taxonomy of psychological situations to illustrate the SIF in concrete terms.

The enactive approach has developed itself as a broader theoretical scope that takes together the ideas expressed by the embodied theory and the application of the nonlinear dynamic systems theory methods in the study of agent and environment interactions (Thompson & Varela, 2017), providing a convergence point from which we can study behavioral, cognitive, affective and social processes. Given this dynamic interplay, the methods provided by the complex dynamical systems theory are relevant to incorporate in the study of personality, as will be described throughout this article. We advocate for the idea that the intersection of regularities, dynamics, and stylistic differences would be in fact, what characterizes psychological traits like personality. Therefore, the question remains on how enactive, embodied, and especially complex dynamical perspectives can explain how these occur by focusing on the dynamics of the processes (i.e., patterns) and interplay of distinct constraints such as organismic and environmental (i.e., intra-individual and situational constraints). In this sense, we are considering a system that consists of an agent (an individual) who is coupled with the environment where it is situated, and therefore, they need to be understood as such a complex dynamical system.

Personality is crucial for understanding the interactions between individuals and their environments, and it is a fundamental component in this individual-environment fit when viewed through the lens of complex, dynamic, enactive, and embodied perspectives. A well-accepted definition of personality in the field of psychology refers to it as coherent and relatively stable patterns of thoughts, affect, behavior, and desires over time and situations (Fleeson et al., 2015; Revelle, 2021). The dynamic approach to personality traits was earlier incorporated in the literature, emphasizing the variability of these traits over time and situations (e.g., Nowak et al., 2002; 2020; Shoda et al., 2002; Fajkowska, 2015; Sosnowska et al., 2019). Recently, enactive approaches to personality have proposed that personality traits would constitute tendencies to an optimal fit or "optimally grip the world" incorporating philosophical and phenomenological accounts (Hovhannisyan & Vervaeke, 2022; Merleau-Ponty, 1945/2013). Similarly, other authors used the ecological approach to propose that personality traits drive active engagement with environmental opportunities for action, or affordances (Satchell et al., 2021).

We aim to emphasize that personality is not a static trait confined to the individual; it is a dynamic component of the broader system that extends beyond the individual. Therefore, the patterns and stylistic differences that constitute personality are integral components of the complex adaptive systems that characterize human beings. This reflection should point out that the traditional way of measuring personality (traditionally with self-report questionnaires) may have to incorporate this dynamic perspective, capturing the fluid and adaptive qualities of personality as it manifests through embodied interactions and dynamic engagements with the world.

Building on different theoretical approaches, we incorporate a broader framework at different levels of complexity to comprehend, measure, and perform meaningful predictive models of higher-order psychological constructs such as personality, and more broadly, human behavior and experience. We aim to incorporate the a) embodied b) dynamic, c) self-organizing, d) soft-assembled, e) synergetic, and f) intersubjective nature of human existence into the understanding and study of personality. We further propose incorporating the view of personality traits as part of the skilled intentionality framework which can help understand how individuals enact the diverse and rich field of affordances they interact with (e.g., Rietveld & Kiverstein, 2014). Additionally, in a practical dimension, we advocate for the use of multimodal measurements —collecting data from various modalities such as behavioral (e.g., movement), physiological (e.g., heart rate variability, skin conductance), or neural activity in addition to self-report to access both, pre- and reflective phenomena as well as personality traits. This combination using embodied sources of information allows us to capture the richness and complexity of behavior (dynamics) and mechanisms underlying those patterns.

2. Enactive, Embodied, and Complex Systems Approaches: Properties and Convergences

2.1. Enactive Approach and Embodiment

The enactive approach is an approximation to thinking about life, embodied minds, and lived experience (Varela et al., 1991/2017; Di Paolo et al., 2017). The enactive perspective postulates an elemental connection between life and the human mind, emphasizing their shared organizational and fundamental properties (Thompson, 2010). Embodiment is essential to the enactive approach, and it emphasizes the inseparable connection between the embodied constitution of the individual, and their coupling with the environment (Varela et al., 1991/2017). The human body engages in perpetual interaction with the physical environment, fostering an interconnected network of feedback loops and sensorimotor couplings, thereby situating sensorimotor life within that immediate environment (e.g., Maturana & Varela, 1991; Pfeifer & Bongard, 2006; Da Rold, 2018).

Individuals are understood not as passive recipients of stimuli, but as active agents who engage in sensorimotor interactions with their surroundings through a dynamic interplay between sensory information, action, cognition, and affect (e.g., Di Paolo, 2021). Therefore, mental processes are embedded in the human bodily constitution's morphological, sensorimotor, and affective systems (Viale et al., 2023). As the body and its emergent functions intertwine, they support the process of self-individuation, allowing it to differentiate from its immediate surroundings and establish itself as an identifiable entity through continuous structural and functional transformations (Di Paolo & Thompson, 2014). Importantly, the boundaries of the individual (agent) are continuously enacted through the process of self-organization, which refers to the exchanges between the individual and the environment without any "central control" while sustaining a form of systemic stability, which will be covered in more detail later (Varela et al. 1991/2017; Galbusera et al., 2019).

According to the central postulate of the embodied hypothesis, cognitive and affective functions emerge from the interaction of an organism with the environment (including other individuals) through sensorimotor processes (Smith, 2005). A broadly accepted conceptualization of embodiment defines three dimensions mutually constraining and enabling, named "cycles of operation" that reflect an agent's (e.g., an individual) life (Thompson & Varela, 2001, p.424; Di Paolo et al., 2017). These three distinctive cycles are 1) Cycles of organismic self-regulation concerning the whole body and involving a basic interoceptive sense of self; 2) cycles of sensorimotor coupling among organisms and their environment, which implicates an "ecological self" (Fuchs, 2020); 3) cycles of intersubjective interaction, involving the recognition of intentionality in behavior and linguistic communication (Di Paolo et al., 2017). In this sense, an addition of the enactive approach is the incorporation of the lived experience that refers to the reflective processes resulting from our embodied experiences in the material world (Varela et al., 1991/2017; Thompson, 2005; Di Paolo, et al., 2017).

These dimensions are relevant to understanding and studying personality because they emphasize the role of the enactive, embodied, and dynamic nature of psychological processes while making explicit the relevance of language, intersubjectivity, and sensemaking in human functioning through the cycles of operation. As a step forward, studying the processes and functions that emerge from the interplay between the individual and the environment requires the incorporation of the methodological toolbox and concepts provided by a nonlinear dynamical systems theory (Thompson & Varela, 2001/2017). This is precisely where these topics converge to offer an integrative and deeper landscape to personality research because, they consider the quantification of the dynamics (patterns and variability) expressed in behavior, affect, and cognition that constitute the stylistic individual differences by which individuals enact the world differently (Hovhannisyan & Vervaeke, 2022).

In the next section, we describe the fundamental properties of complex dynamical systems, and how these properties help to study personality within the enactive/ embodied approach.

2.2. Complex Dynamical Systems Approach

The complex dynamical systems (CDS) approach studies how systems behave and evolve over time, providing methodological tools to study such dynamics (Richardson & Chemero, 2014). Complex systems are understood as interconnected and inseparable from their environments, aligning closely with the principles of enaction and embodiment (Gallagher & Appenzeller, 1999). In psychological science, this translates into the study of dynamic patterns of thought, affect, and behavior dynamically evolving (Nowak & Vallacher, 1998; Nowak et al., 2002; Nowak et al., 2005; Richardson, Dale & Marsh, 2014). For this reason, complex dynamical systems methods can be seen as a toolbox to apply the postulates of the enactive approach incorporating a dynamic and coherent methodological framework.

The CDS approach offers an alternative to reductionist and static models by recognizing how the dynamic interplay between an individual and their surroundings gives rise to emergent properties and patterns (Richardson & Chemero, 2014). In the absence of external influences, complex dynamical systems can exhibit patterns of change at some of the system levels that reflect the inner adjustment of the system components over time (Nowak et al., 2002). The specific attributes or composition of a system do not constrain this non-linear and dynamic behavior. Instead, it is a phenomenon observed across diverse natural systems, ranging from the complexity of weather patterns and chemical reactions to the interplay of cognitive, affective, and behavioral processes in humans (Nowak et al., 2002; Nowak et al., 2020). The CDS framework provides a unifying framework of dynamic, interconnected systems. It provides a lens through which we can reinterpret personality traits and states and invites us to consider personality as a dynamic interplay between individuals and their environments. This resonates with the principles of enaction and embodiment, where an individual's actions and cognition are inseparable from their bodily experiences (Gallagher & Appenzeller, 1999).

There are basic properties within the complex dynamical systems approach, some of which have been mentioned before and converge with the enactive approach. These fundamental characteristics, according to Gallagher and Appenzeller (1999) are first, the existence of interacting components or agents, and they can be either homogeneous or heterogeneous. For example, a neuronal network can be a homogeneous complex dynamical system, while a brain in a body that is at the same time in an environment comprises a heterogeneous complex dynamical system (Richardson & Chemero, 2014). The second property of a complex system is emergence, which refers to the arising of new and coherent structures, patterns, and properties through the process of self-organization in complex systems (Goldstein, 1999; Van Dijk, 2021). In the context of human behavior and personality, emergence can be exemplified as a behavior that shows a coherent pattern that cannot be predicted from the behavior of the components by themselves (separately). The third and fundamental characteristic of complex systems is the self-organization of behavior, being present in most forms of biological organisms. It is possible to observe, for instance, self-organization in the act of walking or in birds flocking; and it has also been exhibited in different forms of synchronization in human systems (e.g., Yun et al., 2012). The concept of self-organization refers to emergent behavioral patterns from the interactions of the different components of the system without a centralized controller and it is especially relevant in coordinated systems as it is the case of animals or individuals interacting together (Richardson et al., 2014).

In the literature, there are additional characteristics that distinguish complex systems and that are interconnected to the previously mentioned: soft-assembly, interaction-dominant dynamics, and nonlinearity. Soft-assembly refers to the context-dependent and emergent behavior that complex dynamical systems exhibit and indicates the individual-environment coupling dynamics (Kloos & Van Orden, 2009). Complex systems are softly assembled because their behavior emerges from the temporary coalition of coordinated agents, components, or elements. Related to this property, some authors also consider the concept of synergy (e.g., Kelso, 2009) to refer to soft-assembled systems, in which a group of structural components is temporarily constrained to act as a unique coherent unit (Richardson & Chemero, 2014). Interaction-dominant dynamics is a property that softly assembled systems exhibit, in this case, the system's behavior is the consequence of interactions among the system components, agents, and, environmental factors with the intercomponent or inter-agent interactions, modifying the dynamics of the elements, environmental factors and the agents themselves (Anderson et al., 2012). Non-linearity refers to systems exhibiting behaviors that are not directly proportional to the inputs, therefore, the output cannot be explained simply by the sum of input elements (Van Orden et al., 2003). In other words, non-linearity defines the feature by which interactions within a system do not follow cause-effect relationships, leading to unexpected behavior or outcomes. Therefore, complex dynamical systems exhibit behaviors that are never explained purely by the addition of their component parts (Richardson & Chemero, 2014). In addition to the previous properties, the phenomenon we introduced earlier as circular causality, is also known as iterativity, iterative causality, or recursiveness, and indicates that the current state of a system will impact the next one (Van Dijk, 2021). This process is self-organizing, and continuous iterations lead to feedback loops that can be self-stabilizing or self-amplifying (Van Geert, 1998, see also Van Dijk, 2021). According to some authors, as a result, from the interaction among lower elements, global recurrent and higher-order patterns emerge, which are known as attractor states (Strogatz, 2001; see also Van Dijk, 2021).

A relevant aspect to consider about complex dynamical systems has been revealed by the study of nonlinear dynamical systems, indicating that such systems can display highly complex and unpredictable behavior, which is particularly pertinent to understanding human behavior (as explained by Richardson et al., 2014). A fundamental insight is that highly complex behavior can arise from very simple rules or systems, provided that the components or agents of the system interact in a nonlinear manner. This means that even simple deterministic nonlinear systems have the capacity to generate extremely complex and unpredictable behavior, which is known as chaotic behavior (Richardson et al., 2014).

While the behavior of such systems is completely determined by quite simple deterministic equations or rules, it can be highly complex and difficult to predict due to the sensitive dependence on initial conditions (i.e., nonlinearity and iterativity). Small differences in starting states can become amplified as the system evolves, making it impossible to predict long-term behavior if the system is chaotic, given the impracticality of measuring initial conditions with perfect precision (which was explained before by iterativity). This principle of chaos has wide implications for understanding human social behavior and in the case of this chapter, personality. It challenges the notion of randomness in behavioral events (Guastello & Liebovitch, 2009), suggesting that seemingly random behavior may not be truly random (Den Hartigh et al., 2017). In this regard, the apparent randomness traditionally assumed in psychology studies thus becomes an empirical question, which is fundamental to interpreting the results obtained in experimental studies that use dynamical measures. For instance, by not negatively labeling the presence of chaos or Entropy, understanding that is part of the dynamics of complex systems. Chaos further underscores the non-obvious connection between past and future events, highlighting how trivial changes can significantly impact time-evolving behavior (Richardson et al., 2014). These insights have led to extensive theoretical discussions of social psychological systems and have found applications in social, personality, and clinical psychology (Richardson et al., 2014; also see Richardson & Chemero, 2014). Moreover, chaos needs to be considered when studying systems' dynamics and it is connected to the following mechanisms.

Two further mechanisms in complex dynamical systems are multistability and metastability (e.g., Kelso, 2012). Multistability refers to "stable states or attractors and the stability of a state depends on how quickly the system returns to a state following a perturbation" (Kelso, 2012, p.906), and this aligns with the traditional dynamic approach to personality. Multistability implies that a system can exist in multiple stable states or configurations of patterns (i.e., attractor states) and small perturbations can cause transitions between those states; such transitions can be influenced by factors such as external phenomena, internal dynamics, or random fluctuation (Kelso, 1995; 2012). The reasons why systems, particularly complex biological systems, exhibit multistability involve several interconnected aspects related to the emergence of synergies formed by self-organizing processes (Kelso, 2012). Non-equilibrium phase transitions, as a basic mechanism of self-organization, give rise to multistability, enabling systems to produce a diverse repertoire of coordinated patterns of behavior (Kelso, 1995; 2009; 2012). Multistability emerges as a crucial aspect in understanding the brain, cognitive function, and psychological processes serving as a promoter of stable individual or collective states (Kelso, 2012).

On the other hand, metastability refers to a state where a system exists at the boundary between stability and instability, representing a balance between the system's components coupling together and expressing their independent behavior (Kelso, 2012). Or, in other words, metastability is a property of coupled dynamical systems where the tendencies to integrate and segregate coexist over time (Kelso, 2012; Bruineberg & Rietveld, 2014). This concept is closely related to chaotic behavior, where systems exhibit sensitive dependence on initial conditions, leading to complex and unpredictable dynamics, as mentioned earlier. In this case, small perturbations in very short time scales (i.e., seconds or milliseconds) can push the system toward one state or another.

Metastability can be useful for understanding how a system (e.g., an individual), interacts with multiple environmental affordances (opportunities for action) simultaneously in a functional and synchronized manner at very short time scales (e.g., Heggli et al., 2021). In a metastable state, the system's dynamics (e.g., behavior, affect, or cognitive states) transition within a certain range, continuously exploring and transitioning between different configurations or states (Tognoli & Kelso, 2013). Metastability allows the brain (or other systems) to flexibly navigate through a set of possibilities (i.e., affordances) without getting stuck in stationary states, which is essential for adaptive behavior, and this process occurs in very short time scales (e.g., milliseconds or seconds) (Kelso, 2012).

The interplay between chaos and metastability reflects the dynamic nature of human behavior. Small perturbations in very short time scales (i.e., seconds or milliseconds) can push the system toward one state or another, resulting in dynamic transitions. However, within the metastable framework, what can be seen as chaotic behavior is not random but rather reflects the system's continuous flexibility and adaptation to changing environmental demands. Therefore, metastability would imply that individuals may exhibit variability in their behavior over time, reflecting adaptation and respond to these changing demands. By continuously exploring and transitioning between different trait configurations, individuals can adjust their behavior to effectively navigate diverse situations and contexts. This ongoing interaction with the environment ensures that the system remains flexible and responsive, expressing the principles of both chaos and metastability in complex adaptive behavior.

However, it is relevant to mention that chaos is not adaptive in excess, and there may be similar nuances in metastability as well, where probably there are ideal limits for such dynamic states. When the system becomes excessively sensitive to perturbations, it may lead to maladaptive chaotic behavior where the individual cannot stabilize in a functional state. In the field of personality, this can be exemplified by individuals with high levels of Neuroticism (low emotional stability) who might experience excessive fluctuations in emotional states (with the respective physiological/embodied correlates), relating to increased anxiety and mood disorders. Similarly, when metastability fails to achieve a balance, it can result in either rigidity, where the system is unable to adapt to new conditions, or excessive instability, where the system fails to maintain coherent behavior. This highlights the importance of a balanced interaction between stability and flexibility for optimal functioning. Understanding these dynamics is crucial when conducting experimental research, interpreting the results expressed in dynamic measures in the light of psychological constructs such as personality; and also, developing interventions that can help individuals better manage their adaptive responses to environmental challenges.

2.3. Functional Synchronization: A complex dynamical approach to human functioning

The concept of functional synchronization employs the fundaments of the CDS theory to provide an understanding of human functioning at different levels of analysis (Nowak et al., 2017). In this way, it provides a framework to explain the emergence of intra-individual and interpersonal dynamics, as well as personality (e.g., Nowak et al., 2005; Vallacher et al., 2015). People naturally synchronize their behavior in time, influenced by situational and interpersonal factors (Nowak et al., 2020). The functional synchronization model explains how functional units emerge from the synchronization of lower-level elements in different domains of human experience, such as brain, mind, and social systems (Nowak et al., 2017; 2020). The core idea is that functional units are coherent structures that perform tasks by assembling and disassembling elements that influence each other in time (i.e., interaction dominant dynamics). Synchronization then, operates at various levels, from neural activity to group dynamics, enabling the integration of information and the emergence of functions (Nowak et al., 2017).

Synchronization can be understood from two perspectives: the system level and the element level (Nowak et al., 2017). At the system level, synchronization involves the temporal coordination of states or dynamics within a system, resulting in observable patterns of behavioral matching during interactions (Bernieri, 1988). This coordination is exemplified by phenomena such as in-phase neural activations (Buzsaki, 2006), coordinated muscle group activation (Thelen, 1985), and the alignment and integration between cognitive and affective states leading to behavioral changes (Thagard & Nerb, 2002; Nowak et al., 2017). In the context of personality, system-level synchronization refers to the coordination of overall states or dynamics within the psychological system of an individual. It would entail the temporal alignment and coordination of patterns of cognition, affect, and behavior (actions). For example, a person with high levels of Extraversion may exhibit a consistent alignment between their socially oriented behavior and positive affect across diverse social situations and over time. This system-level synchronization contributes to the stable manifestation of Extraversion as a personality trait over time.

At the element level, synchronization refers to the mutual influence among individual elements within a system (Singer, 1999). This mutual influence is evidenced by congruent signals between specific muscles (Bernstein, 1967), mutual interactions within attractor neural networks (Zochowski et al., 1993), and sets of thoughts supporting specific attitudes (Abelson et al., 1968). In essence, synchronization at the element level involves the coordination of individual components to achieve coherent behavior or patterns of activity within the larger system (Nowak et al., 2017). In the context of personality, element-level synchronization would involve the integration and coherence of psychological elements on a smaller scale such as perception, thoughts, emotions, and physiological responses to constitute stable personality traits. For instance, a highly agreeable individual may exhibit a coherent alignment between empathetic thoughts, compassionate emotions, and gregarious and prosocial behavior, which are all synchronized and give coherence to Agreeableness as a personality trait. Synchronization can be further differentiated into at least three categories depending on the time-lag (Altmann, 2013; see also Scheidt et al., 2021): No time-lag: Indicates perfectly synchronous behavior. Synchronous behavior with time delay (time-lag): Reflects alignment that is not simultaneous. Convergence and adaptability: Indicates increasing similarity across time.

Functional synchronization relies on both multistability and metastability. Multistability explains stable states or attractors, while metastability enables flexible transitions between these states, allowing the system to adapt and respond to changing environmental demands in a synchronized manner. This continuous exploration and transition between different configurations support adaptive behavior and effective navigation of various situations and contexts. Functional synchronization then, can operate at different levels of analysis. If we consider the individual and social domains, intrapersonal synchronization refers to how an individual's internal processes, including behavioral, cognitive, and emotional states (among others), synchronize and self-organize to produce coherent patterns over time sustaining systemic stability (Kelso, 1995), and such synchronizing processes are related to personality traits. For example, a previous experimental study exhibited that the complexity/flexibility (Entropy), stability, and regular (deterministic) patterns in body motion dynamics were decreased in highly neurotic (low emotional stability) individuals during specific self-referencing topics (e.g. when talking about their socioemotional life) (Arellano-Véliz, et al., 2024b). In this case, this personality dimension, which is characterized by the facets of anxiety, anger/hostility, depression, self-consciousness, impulsiveness, and vulnerability, seems to have a similar 'unstable' embodied correlate and decreased complexity in body motion dynamics. This example reflects how embodied accounts are in deep alignment with the relatively stable patterns of behavior and affect over time (i.e. personality traits), whereas these intra-individual dynamics are highly context-dependent and softly-assembled (e.g., Van Dijk, 2020). Similarly, other studies exhibited how internal states can be affected by interactions with others in the regulation (Galbusera et al., 2019) or changes in affective states (Arellano-Véliz, et al., 2024a); how task constraints can affect intra-individual gestures and speech integration and synchronization in infants (De Jonge-Hoekstra et al., 2021). Overall, it is possible to see that personality traits are part of a complex dynamical system: an individual-environment coupled system.

On the other side, at the interpersonal level, synchronization in dyadic interactions (or group dynamics), is an emergent property that was not present before through the coordination in time of behavior, affect, cognition, physiological states, or other modalities (e.g., Galbusera et al., 2019; Vallacher & Nowak, 2007; 2009). Some researchers propose that interpersonal synchronization serves as a bridge between social interactions and the formation of social relationships and can serve as a mechanism of self-other integration (Heggli et al., 2021). Through synchronization, individuals establish rapport and connection, which can further influence the trajectory of their personality traits (Tschacher et al., 2018; Nowak et al., 2020). The mutual influence in social interactions promotes the development of shared internal states that facilitate synchronization, where the emergent dyadic system tends to reduce its degrees of freedom as the individual systems become more coupled (Riley et al., 2011; Tschacher et al., 2018). The dyadic system emerges through interpersonal synergies or higher-order control systems resulting from the coupling of the degrees of freedom within the systems of two or more individuals (Riley et al., 2011). Some authors further proposed that with ongoing interactions, the emergent internal states become embedded as attractors (recurrent patterns) in the individuals' systems, and this is referred to as the interpersonal synchronization model (Nowak et al., 2020). These attractors would represent stable states toward which a system tends to gravitate over time, constituting the foundation for the emergence of patterns that can serve as "ready-made" control parameters for future interactions with others, promoting consistent social behavior (Nowak et al., 2020).

However, it is important to keep in mind that intra-personal and interpersonal dynamics are mutually influenced by the mutual organism-environment interactions. Therefore, these borders are not given but constantly enacted by the processes of self-organizing dynamics (Thompson & Varela, 2001/2017; Galbusera et al., 2019). In this way, personality traits would be both, influencing the occurrence of behavioral patterns and the maintenance of certain environments and also being influenced by environmental and social interactions in the regularities observed in the individual dynamics.

This is certainly an approximation to the enactive and complex fundaments of personality traits, where the phenomenon of functional synchronization serves to understand how multiple components across different levels —individual, interpersonal, and environment– concurrently synchronize leading to coherent states. Such synchronization occurs through the process of soft-assembly wherein interactions with environmental and situational constraints continually shape the emergent dynamics.

2.4. Complex dynamical systems applied to personality traits

Complex dynamical approaches to personality and individual differences are not new. These approaches propose that individual differences can be understood in dynamic (e.g., Shoda et al., 2002 Sosnowska et al., 2019), interpersonal terms, and at different levels of analysis (e.g., Nowak et al., 2002; 2020; Fajkowska, 2015; Back, 2021). Nowak et al. (2002) proposed an approach to the emergence of personality through the scope of dynamic systems, which evolved later on to an approach to social interactions and interpersonal synchronization (Nowak et al., 2020). In essence, the idea is that a dynamical system is composed of a set of dynamic variables (x) that change over time, and there are control parameters (r) that influence those variables. This idea was used to model human dynamics where the dynamical component (x) can be interpreted as behavior, therefore, changes in x represent variability in the intensity of such behavior. The control parameter, r, would reflect internal states –such as affect, mood, or a combination of patterns of cognition/affect/behavior/desires, or personality traits– that shape the individual's behavioral patterns (fluctuation in x over time) (Nowak et al., 2020).

According to the traditional dynamical systems approach to personality traits and states, a trait is understood as the baseline as the core of it, and a state, variability around it (e.g., Nowak et al., 2002; Sosnowska et al., 2019). This strongly builds on the dichotomy of a relatively fixed internal structure and a 'fluid' environment which feeds into this structure as a perturbation, making the system dynamic, which serves to grasp the regularities and variability of personality. This separation might not be necessary if we consider how fluid behavior, affect, and cognition are, constantly affected by environmental constraints through circular cycles of operation, or reciprocal causality (Thompson & Varela, 2001; Fuchs, 2020). This means that the relationship between organism and environment is reciprocal, where both are mutually affected by the other however, this interaction is not necessarily symmetrical (Thompson & Varela, 2001). Therefore, the network we are looking at consists of elements that can only arbitrarily be assigned to the 'internal' or 'external' and critically depend on each other, for example, through the interpersonal synergies mentioned previously (Riley et al., 2011). This would mean that the observed fluctuations might come from the tendency of this system to move toward critical (i.e. unstable) states rather than stable states, which refers to the concept of self-organized criticality (Goldstein, 1999).

Rather than suggesting direct causation by personality traits in behavior, we embrace the proposition that individuals develop synchronization-related skills and habits that are socially rewarding and stimulating, which are reinforced over time (e.g., Nowak et al., 2020; Satchell et al., 2021). These behaviors become strong attractors within the individual's behavioral system, reinforcing and further developing these tendencies over time. This dynamic process contributes to the formation of traits that we recognize as the Big Five personality traits (or other classifications). These traits are subsequently identified through personality assessments designed to capture self-reported and self-observed behavioral patterns. Furthermore, our conceptualization and recognition of these traits are influenced by the labels present in the literature we use to describe the regularities observed in the behavioral, affective, cognitive, and social patterns. This idea implies that personality traits are not fixed entities but dynamic states emergent through the mutual interaction of internal and external exchanges.

If we apply the properties of CDS to personality, first the interacting components of such a heterogeneous complex system would be, for example, the whole body of an individual and therefore a sensorimotor system that is coupled or synchronized with the environment (which could also be other people), perceiving the environmental affordances or opportunities for action (Gibson, 1980), displaying actions accordingly and impacting the environment in which the individual is situated (Satchell et al., 2021). If we take into consideration the definition of personality, then we could say that those components can be internal states such as thoughts, affect, and desires; as well as behaviors that make up consistent patterns over time –they have a degree of coherence and synchronization (Nowak et al., 2020). All of these components are highly sensitive to environmental constraints (Klimstra et al., 2018); and, therefore, are softly-assembled. In the case of dyadic systems as interconnected networks, individuals interact and influence each other's behaviors circularly (e.g., Van Dijk, 2020). Each person within the network represents an agent, and their interactions contribute to the dynamics of the overall system. The interactions could involve communication, influence, or the exchange of ideas.

Furthermore, nonlinear dynamics, imply that slight variations in an individual's experiences or environments could result in significant alterations to their personality traits' profiles (e.g., Geukes et al., 2017). Consequently, personality traits might exhibit sudden shifts or transformations that deviate from predictable patterns due to the inherent sensitivity of complex systems to initial conditions. Self-organized criticality, or the emergence of critical states, arises when a system is far from its equilibrium point (e.g. Plentz et al., 2021). This idea implies that personality traits are not fixed entities but rather manifest as points of stability amidst ongoing variability (e.g., Fleeson et al., 2015; Sosnowska et al., 2019; Revelle & Wilt, 2021). In this view, personality traits vary over time within a certain range responding to individual differences, and are influenced by various internal and external factors that propel the system into states of dynamic equilibrium (Wilt et al., 2017).

Besides, personality traits can be subject to multistability and metastability. In a multistable system, different attractor states coexist, and the system can transition between these states under the influence of internal or external perturbations (Kelso, 2012), and it is similar to the "ready-made" control parameters mentioned before. Multistability can be applied to personality by considering how individuals may exhibit multiple stable patterns of engagement with affordances, each corresponding to a different personality trait or behavioral tendency. For example, an individual may have distinct patterns of engagement with social affordances (e.g., engaging in social interactions) compared to non-social affordances (e.g., solitary activities), reflecting different aspects of their personality such as Extraversion or introversion. Furthermore, personality traits would be adapting to ever-changing contexts and experiences while maintaining consistency and coherence over time. In this case, since multistability involves multiple stable states or attractors, for example, a high level of emotional stability (low Neuroticism) would imply that the stability of different emotional states is robust and the system would quickly return to them after perturbations. Multistability can explain how personality traits develop consistency, coherence, and regularities, and evolve over the lifespan. Multistability could also involve transitions between different trait configurations, akin to switching between attractor states (e.g., Heggli et al., 2021).

Metastability can be applied to personality by considering how individuals may exhibit transient patterns of synchronization or engagement with affordances that fluctuate over time, but metastability should be considered as a phenomenon occurring at short time-scales. For example, an individual may experience fluctuations in their engagement with environmental affordances due to changes in mood, motivation, or situational context. These transient states may reflect the dynamic interplay between stable personality traits and contextual factors, suggesting a metastable nature of personality expression in different situations. Metastability suggests that stable states are not rigid but adaptable. In personality, this translates to trait flexibility (Fleeson et al., 2015; Sosnowksa et al., 2019), and foremost, to the behavioral, affective, and cognitive patterns that configure those traits (the timescale would be rather small). Individuals may adapt their behavior based on situational demands, social cues, or personal goals (Jones et al., 2017). Metastability allows for context-dependent shifts in personality expression, emphasizing the dynamic nature of traits. In the context of personality, metastability implies that personality is characterized by dynamic fluctuations and transitions between different trait states. Presumably, the range of transitions is different for distinct personality traits and their facets. For instance, the facet anxiety of the trait Neuroticism can have more fluctuation and transitions than the facet self-discipline of the trait Conscientiousness. Metastability further incorporates the complexity of trait interactions, where different traits may interact and influence each other in nonlinear ways, leading to emergent patterns of behavior that fluctuate and evolve over time. And, despite its dynamic nature, metastability also implies a degree of stability and resilience within personality. Whereas individuals may experience fluctuations in their behavior and traits, they ultimately maintain a sense of identity and coherence over time.

Both multistability and metastability may have implications for understanding personality development over the lifespan. Individuals may transition between different trait states as they encounter new experiences and undergo personal growth, leading to shifts in their overall personality profile (McCrae et al., 2020). However, it is still necessary to understand underlying mechanisms and be aware that these changes in personality states and traits, are rather small and may tend to be relatively stable over time. The most significant personality changes occur during the transition to early adulthood, a period coinciding with the completion of brain development, which would be a critical period to conduct studies (Sowell et al., 2001; McCrae et al., 2020). In this sense, also major life events or experiences may lead to shifts or changes in their personality over time. These shifts may not be immediate but may occur gradually as the individual adapts to new circumstances or integrates new experiences into their self-concept.

By incorporating a complex dynamic and enactive approach, it is possible to better capture the dynamics of personality traits and their embodied correlates over time. Personality would be seen then as a dynamic interplay between the organic and agentic constitutions of human bodies and the surrounding environment. This interplay results in the emergence of temporal patterns and dynamics across social, individual, and material dimensions. Despite the context-sensitivity, soft-assembled nature, and dynamic fluctuations of these processes, we observe consistent global regularities and individual differences in behavior, affect, and cognition. We assert that the intersection of regularities, dynamics, and stylistic differences characterizes personality. In the next section, we explore how personality traits can be understood in the context of engagement or synchronization with multiple affordances.

3. Sensorimotor coupling, personality traits, and affordances

In this section, we incorporate the Skilled Intentionality Framework (SIF, Bruineberg & Rietveld, 2014; Rietveld et al., 2018) that integrates enactive and embodied approaches focusing on opportunities for action or affordances and it is a suitable integrative framework (e.g., de Vries et al., 2016; Back et al., 2023), supporting the fundament developed throughout this chapter in the context of personality traits. Affordances are central to understanding the embodied mind and individual-environment coupling (Gibson, 1979). Affordances are the potential actions or opportunities that the environment offers to an animal or human based on the individual's capabilities, intentions, experiences (Gibson 1979; Chemero 2003), and personality. Affordances are relational, meaning they depend on the context and the individual's perceptions, and they arise from the interaction between an agent's abilities, skills, and the features of the environment (Rietveld & Kiverstein 2014). For example, an apple affords to eat, a mountain affords climbing, and a person affords to talk. However, the inclination to perform each of these actions will be subject to individual differences and situational constraints; they will not be perceived and acted upon equally. In this sense, the field of affordances is the set of all affordances that are available to an individual at a given moment (Rietveld et al., 2018); whereas a landscape of affordances would be the affordances available within an ecological niche (Bruineberg & Rietveld, 2014).

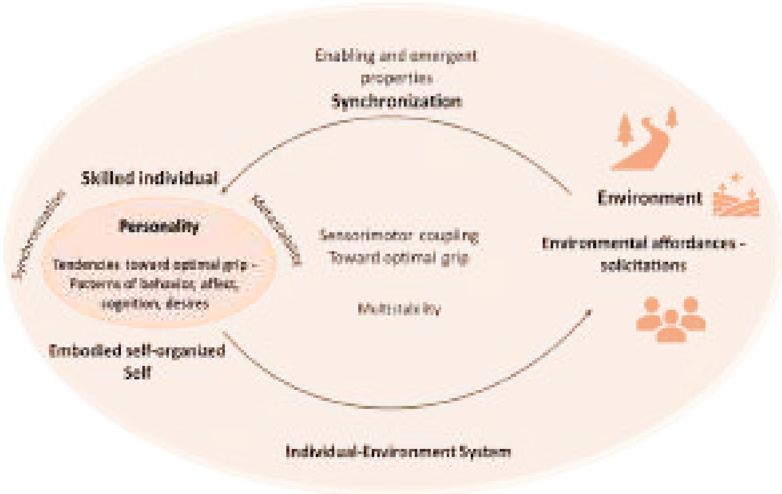
The field of relevant affordances can be seen as a continuum of all possible actions available to an agent within its environment; and it is dynamic, which means that changes as the agent, the environment, and situations change (Rietveld et al., 2018). As a side note, the concept of affordances comes from the ecological psychology tradition, which has theoretical differences with the enactive approach. Some of the fundamental differences between both frameworks are that the ecological approach emphasizes the nature of the environment that animals perceive and act upon; whereas the enactive approach focuses on the organism as an agent, incorporating the process of sensemaking as well (Baggs & Chemero, 2021). We will not dive deeper into these distinctions, since both frameworks can be complemented to enhance the types of explanations we pursue. Moreover, in order to fully understand phenomena such as the patterns that characterize personality, we need concepts from the enactive approach such as agency, sensemaking, and intersubjectivity in our becoming as human beings (Di Paolo, 2021).

Skilled intentionality is defined as “the kind of intentionality an individual exhibits when acting skillfully in a familiar situation” (Bruineberg & Rietveld, 2014, p.2). Skilled intentionality is characterized then, by selective engagement with multiple affordances tending toward an optimal grip within a field of affordances (Bruineberg & Rietveld, 2014; Rietveld et al., 2018). This process would be plausible in the context of multistability and metastability through the coherent and synchronized coupling with multiple affordances leading to transitions between states across different time scales and situations. It would be the coherence and engagement with these multiple affordances that lead to individual-environment relative systemic equilibrium (Rietveld et al., 2018), for which the phenomenon of synchronization is functional to achieve and sustain equilibrium. This perspective implies that personality traits would be part of the skilled intentionality that individuals possess, making up differentially “skilled individuals”, and acting as drives to start a process of sensemaking while exploring opportunities in the environment: affordances or solicitations. Specifically, affordances are opportunities for action in the context of a form of life (e.g., humans) or within an ecological niche (Bruineberg & Rietveld, 2014). Solicitations are affordances relevant within a specific situation and, therefore, stand out as relevant for a situated individual, generating readiness in bodily states for action, or embodied readiness (Rietveld & Kiverstein, 2014; Bruineberg & Rietveld, 2014; Rietveld et al., 2018). Embodied readiness is part of the organism-environment reciprocal causality previously mentioned, and it involves comprehensive and reciprocal sensorimotor cycles of perceiving, acting, and sensemaking.

In this way, going back to the enactive definition of personality traits as different ways of optimally gripping the world (Hovhannisyan & Vervaeke, 2022), the drive toward optimal gripping would be given by the engagement with multiple relevant affordances through metastable states that are coherent and relatively stable over time. This idea implies that individual differences emerge through individual and environment coupling (e.g., Satchell et al., 2021). The skilled individual in the context of personality traits, will be given by metastable attractors (Heggli et al., 2021) of each trait or dimension, which represents their range of fluctuation and transitions while exploring multiple opportunities for action (relevant for each trait). In this way, individual differences in personality traits suppose different engagement in a field of relevant affordances and differential embodied readiness. In Figure 1, we represent an individual-environment system incorporating the concepts discussed throughout the chapter, which can take the form of a dyadic system.

Furthermore, the cycles of organismic self-regulation are fundamental for the skilled intentionality framework as they provide the foundation for individuals to perceive and respond to affordances in their environment. The attunement by which individuals engage with environmental affordances involves recognizing and responding to the opportunities for action provided by the environment through sensorimotor coupling, the continuous feedback loop between sensory information and motor behavior (Rietveld et al., 2018). Such sensorimotor coupling enables individuals to enact their intentions and engage with these affordances dynamically and adaptively. By coupling their actions with environmental features, individuals shape and are shaped by their surroundings, continuously refining their interactions based on environmental feedback. Through the perception of verbal and non-verbal cues in others, individuals can navigate social affordances, such as opportunities for cooperation, competition, and affiliation, which further contribute to the development and expression of personality traits. In this sense, the responsiveness to these social affordances is selective (Rietveld, 2012), to the extent that individual differences such as personality traits will play a role in it. For instance, a highly extroverted individual may have a very developed set of metacognitive skills, which increases the likelihood of recognizing social cues in others; furthermore, by acting upon social affordances such metacognitive skills set will be enriched by the feedback received on each social engagement.

Figure 1. Example of a hypothetical individual-environment system from an enactive and complex dynamical systems perspective



Note: The figure represents an individual-environment system. The embodied and skilled individual is characterized by a unique configuration of personality traits that constitute tendencies toward optimal grip (Rietveld, 2013; Bruineberg & Rietveld, 2014). The individual actively engages with the environment, perceiving multiple relevant affordances present within it, which occur according to their own constitution. Solicitations are affordances specific to situations. Behaviors enacted by the individual generate more affordances or solicitations within the environment, shaping the ongoing sensorimotor individual-environment coupling. Synchronization (or individual-environment coupling) is an emergent property. The environment can include another individual or group of individuals, in which case the *system becomes a dyadic or social system. In dyadic systems, each embodied and skilled individual, with different configurations of personality traits, actively enacts the situation, perceives multiple relevant affordances or solicitations, and displays behaviors that influence the interaction partner through sensorimotor cycles. The behaviors performed by one individual constitute affordances or solicitations for the conversation partner. Interpersonal synchronization emerges from the interaction and simultaneously influences the sensorimotor experience of each interacting partner. In both individual-environment and dyadic systems, metastability indicates the stability of states over time while remaining susceptible to transitions to alternative states. Metastability involves self-organizing processes that facilitate the integration and segregation of cognitive processes, physiological responses, emotions, and other processes at a micro-level time scale (i.e., milliseconds, seconds, minutes) (Kelso, 2012; Bruineberg et al., 2021). These processes influence the individual's engagement with their environment. The concept of multistability reflects the system's capacity to exist in multiple stable states. Through the interaction between the individual and their environment, various configurations or patterns of behavior may emerge, each representing a distinct stable state within the dynamic system. These emergent patterns contribute to the complexity of the individual's experiences and behaviors within their environment (inspired by Bruineberg & Rietveld, 2014; Rietveld et al., 2018).*

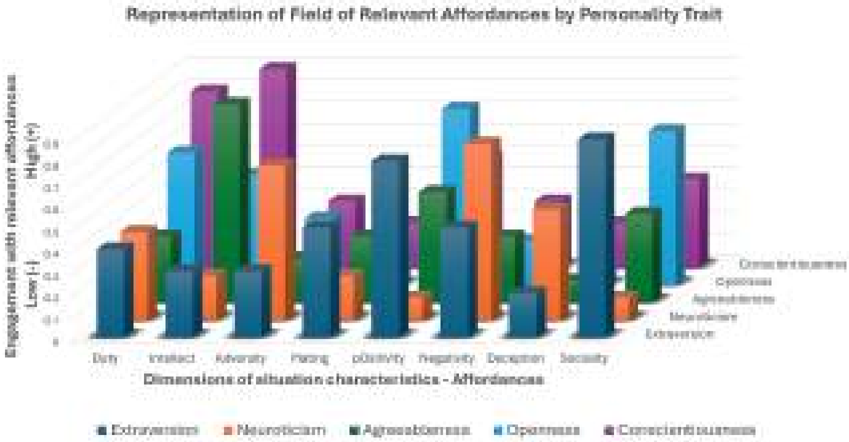
4. Big Five Personality Traits: Illustration of the Enactive, Complex Dynamical Systems and Skilled Intentionality Framework Approaches

As developed throughout the chapter, individuals continuously and selectively perceive affordances and engage with them. The emergence of self-organized patterns that constitute personality traits would be involved in a circular way in how individuals engage with affordances, possibly by developing skills that are rewarding and stimulating for them, in line with the SIF, which become strong attractors within the individuals' behavioral system. This dynamic process would reinforce and further promote engagement with such affordances over time and situations (e.g., Satchell et al., 2021; Nowak et al., 2020). The goal of this section is to provide a concrete visualization of how the SIF can be applied to the Big Five personality traits. For this, the tendencies toward an optimal grip are visualized in terms of engagement with multiple affordances by each trait. In this case, affordances or solicitations are represented using an existent taxonomy of major dimensions of psychological situations in the literature. It is important to note that the taxonomy presented below was chosen for illustrative purposes, its predominance in personality literature, and its value as a validated assessment tool to complement experimental or ecological studies.

There are several working models on psychologically relevant situation taxonomies available in the literature. To exemplify how individual differences in personality traits can represent a differential tendency to engage with affordances and create diverse optimal grips or individual-environment couplings, we will discuss the DIAMONDS taxonomy (Rauthmann et al., 2014). DIAMONDS refers to eight categories of relevant psychological situations for individuals, Duty, Intellect, Adversity, Mating, pOsitivity, Negativity, Deception, and Sociality (Rauthmann et al., 2014). Importantly, in the original work by Rauthmann et al. (2014), they present these dimensions composed of self-reported questions about how individuals perceive and evaluate situations. For example, people are asked to rate to what extent a situation was pleasant or uncomfortable. These dimensions are positively associated with behavioral cues described in behavioral assessment tools (Riverside Behavioral Q-Short Version 3.0, RBQ; Funder et al., 2000). For instance, the pOsitive dimension was positively associated with behaviors like laughing frequently and smiling frequently in a multicultural Western sample; however, the taxonomy does not incorporate directly measured behavior (Rauthmann et al., 2014). For the illustration presented in this chapter, we would consider these dimensions as types of situations used to represent "types or sets of affordances" that individuals are more or less likely to perceive and engage with. This taxonomy provides an approximation of how affordances are embedded in each category, representing areas in the field of affordances. Its comprehensive categorization of situational factors effectively captures a broad range of situational contexts that are relevant to understanding how individuals engage with their environments, and align closely with personality traits (Rauthmann et al., 2014).

In this exemplification, as presented by Rauthmann et al., (2014), Duty would reflect affordances for fulfilling rational thinking, responsibilities, or work-related behaviors. Intellect would reflect affordances for engaging in intellectual challenges, problem-solving, and expressing new ideas. Adversity would reflect situations related to conflict. Mating would represent affordances related to forming intimate relationships and fulfilling romantic and sexual goals. pOsitivity would represent situational affordances related to positive affect, pleasant, and social-affiliative behaviors. Negativity would reflect situations associated with unpleasant behaviors. Deception would represent situations or cues that present opportunities for antagonistic behaviors. Finally, Sociality would reflect affordances for social interaction, affiliation, and cooperation with others in various contexts. Note that this correspondence of the DIAMONDS taxonomy with the SIF is hypothetical, and even though the authors mention the concept of affordances in their study, directly observed behavior is not measured (instead it is self-reported), which is a relevant element to keep in mind in future ecologically guided studies. For readers interested in detailed information about the taxonomy, consult Rauthmann et al. (2014; 2017). Based on this illustration, Figure 2 presents how each Big Five personality trait would be situated in a field of relevant affordances defined by the DIAMONDS dimensions. The Figure represents a distinct probability of engagement with relevant affordances for each personality trait.

Figure 2. Representation of a field of relevant affordances for each personality trait using the DIAMONDS taxonomy for psychologically relevant situations.



Note: This figure is a hypothetical and schematic representation of a field of relevant affordances (x-axis), where the relevant affordances correspond to the DIAMONDS taxonomy for psychologically relevant situations for illustrative purposes (Rauthmann et al., 2014). The z-axis represents the probability of engaging with relevant affordances (from lower to higher), and the y-axis represents each Big Five personality trait. The figure illustrates how individual differences in personality traits would represent a distinct probability of engagement with relevant affordances or solicitations. In this representation, the DIAMONDS is a categorization, it can be seen as specific types of affordances that are embedded in this taxonomy. In this sense, each category of the taxonomy would correspond to areas in the field of affordances.

4.1. Extraversion

Extraversion is defined as a personality trait characterized by sociability, assertiveness, a tendency to seek out social interactions (Costa & McCrae, 1992a, Costa & McCrae, 1992b), and to experience positive affect (e.g., Fleeson et al., 2002). Therefore, in the example (Figure 2), extroverts might exhibit more attunement to social affordances, such as opportunities for social interaction and positivity (Augustine & Hemenover, 2008). In this way, environments offering chances for social engagement and stimulation may be perceived as solicitations that are enacted (acted upon), which in the case of introverts might not be considered to engage with. Highly extroverted individuals' skilled intentionality is exhibited in the creation of opportunities for themselves and for others to attune to specific behaviors, as has been shown in previous experimental studies (e.g., Arellano-Véliz et al., 2024a). For instance, an extroverted person, with a rich repertoire of social skills can create a positive feedback loop. Their engaging behaviors, such as smiling, making eye contact, and overall sending relevant prosocial and visible bodily cues (e.g., Cuperman & Ickes, 2009; Jiang et al., 2023) increase the likelihood of receiving positive responses. Such behavioral cues –active body– would be functionally and dynamically synchronized with the environment where they are situated tending toward an optimal grip (Rietveld et al., 2018; Arellano-Véliz et al., 2024a). This leads to a social environment where people around them are more likely to engage in similar behaviors, actively shaping the field of social affordances.

Therefore, the extrovert is not only attuning to this field of social affordances but is also creating them for others around, promoting a reinforcing and reciprocal cycle (Augustine & Hemenover, 2008; Arellano-Véliz et al., 2024c). In this case, as mentioned earlier, such circular or reciprocal causality is not symmetrical (Thompson & Varela, 2001), as extraverts would play an agentic and active role. Introverts may be less attuned to certain social affordances, especially those related to extensive social engagement (Augustine & Hemenover, 2012). Their skilled intentionality might be more focused on internal states and less on actively creating external social opportunities (Oishi et al., 2015). In a group setting, introverts might not enact social affordances in the same way as extroverts, however, they might perceive relevant social affordances in one-to-one interactions, and attune to them, leading to different social dynamics (Arellano-Véliz et al., 2024c). Therefore, introverts actively enact those affordances creating and maintaining quieter environments as they are less driven by external stimulation (Hills & Argyle, 2001; DeYoung, 2013), for example, research suggests that introverts prefer natural environments which are also linked to greater well-being to them (Oishi et al., 2015).

4.2. Neuroticism

Neuroticism or emotional stability, is characterized in the literature by the facets of anxiety, anger or hostility, depression, self-consciousness, impulsiveness, and vulnerability (Costa & McCrae, 1992a; Costa & McCrae, 1992b). High Neuroticism (low emotional stability) would perceive relevant affordances that trigger negativity (Rauthmann et al., 2014, see Figure 2), which in turn would promote an embodied readiness for action in situations perceived as stressful (solicitations). They might be more attuned to perceive situational elements as negative and threatening. This embodied readiness implies a sensorimotor cycle of perceiving, acting, and sensemaking processes. Thus, highly neurotic individuals might embody heightened emotional responsiveness and sensitivity to potential threats, shaping their emotional patterns (Watson, 2001; Hovhannisyan & Vervaeke, 2022). This trait is thought to optimize security (DeYoung, 2015). Neurotic individuals may exhibit sensorimotor processes that promote experiencing emotions like fear or anxiety in uncertain situations, leading them to approach with caution or defensiveness (DeYoung, 2013). In this way, they may perceive relevant affordances related to negativity or negative affect and to act upon them (see Figure 2) (Ng, 2014).

In this sense, the literature suggests that Neuroticism is related to anxiety disorders, and mood disorders like social anxiety and depression (Ormel et al., 2013; Barlow et al., 2014; Li et al., 2020; Li et al., 2024), as well as some personality disorders (Bowden-Green et al., 2020). From the SIF, it would be the tendency to perceive and enact negative affordances and solicitations as relevant that makes up their tendency toward individual-environment optimal grip. Emotional stability, on the other hand, can be seen as a tendency toward lower emotional reactivity and less activation in the face of stressors (Hovhannisyan & Vervaeke, 2022). This trait is believed to optimize a sense of security and stability (DeYoung, 2015; Hovhannisyan & Vervaeke, 2022). Emotionally stable individuals exhibit less likelihood to experience emotions like fear or anxiety in uncertain situations, resulting in a tendency to approach challenges with calmness and composure (DeYoung, 2013). In the literature, high emotional stability is considered a protective factor related to a decreased likelihood of experiencing mood and personality disorders (e.g., Li et al., 2020; Li et al., 2024). Consequently, they may be less inclined to perceive negative affordances or solicitations as relevant, contributing to their ability to maintain an optimal grip on their environment.

4.3. Openness to Experience

Openness to experience shares variance with Extraversion and it is defined as one of the broadest dimensions of personality which is characterized in the literature by tolerance of ambiguity, drive for variety, aesthetic sensitivity, intellectual curiosity, and eccentricity, among others (McCrae, 2004; DeYoung, 2015). From the SIF, this trait would be viewed as the dynamic interplay between an individual's drive to seek out and engage with a very diverse range of affordances due to its drive for cognitive exploration (DeYoung, 2015; Raya et al., 2023).

The trait's emergence and expression may involve the self-organization of a wide variety of embodied exploratory behaviors, affective responses, and cognitive patterns in response to varying environmental stimuli they perceive, engage with, create, and sustain (e.g., Schretlen et al., 2010; Samuel et al., 2023). Soft assembly in this context would involve flexible coordination of sensory input and motor responses, allowing for adaptive and exploratory behaviors, engaging with relevant affordances, where the body's movements contribute to the exploration of them (DeYoung et al., 2011). Their perceptual and cognitive exploration processes are attuned to changing contexts, allowing for a fluid and metastable integration of new information and experiences, this would facilitate the soft assembly of knowledge structures, allowing for the integration of diverse information (DeYoung et al., 2011; DeYoung, 2015; Raya et al., 2023).

In the representation (Figure 2), Openness would be attuned to affordances and solicitations linked to positivity and intellect, and less relevant would be those related to negativity and deception. Therefore, for Openness to experience, skilled intentionality would refer to how individuals actively shape their environment through engagement with their material, social, and personal world, for instance by displaying innovative and creative behaviors. Such active individual-environment coupling would tend toward Openness to experience optimal grip (Rietveld et al., 2018). On the other hand, low Openness to experience can be seen as a tendency toward less exploratory and more conventional behaviors in response to a reduced field of affordances compared to high Openness to experience (McCrae, 2004; De Young, 2012; Hovhannisyan & Vervaeke, 2022). Individuals with low Openness may tend to familiar activities, and affordances related to novelty would not be perceived as relevant, being less attuned to exploratory affordances. Their skilled intentionality might be more focused on maintaining familiar activities, contributing to perceiving comfort, predictability, and stability as relevant affordances.

4.4. Agreeableness

Agreeableness is defined as the tendency toward cooperation, altruism, compassion, and prosocial behavior (Costa et al., 1990; De Young, 2015). Meta-analyses suggest that it is a hierarchical construct, the meso-level aspects of compassion and politeness (e.g., Crowe et al., 2018; Judge et al., 2013; Ludeke et al., 2019, see also Wilmot & Ones, 2022). The compassion aspect is composed of the facet of altruism (nurturance, Wiggins, 1991) and tendermindedness (or sympathy, Goldberg, 2006), and reflects drives for social attachment, interpersonal concern, and empathy (DeYoung, 2015; Wilmot & Ones, 2022). The politeness aspect, composed of straightforwardness (also known as morality, Goldberg et al., 2006), modesty, and cooperativeness (or compliance, Costa & McCrae, 1992b), encompasses tendencies to suppress and avoid aggressive or norm-violating impulses and behavior, being linked emotional regulation and the behavioral inhibition system (DeYoung, 2015; Smits & Boeck, 2006; see also Wilmot & Ones, 2022). Agreeable individuals would be attuned to prosocial affordances and solicitations within the social field of relevant affordances, exhibiting behavioral patterns related to self-transcendence (aspirations from growth), contentment (acceptance of life circumstances), positive relationships, coordination with others to achieve goals, work investment, social norm orientation, cooperation, empathy, and prosocial behavior (Wilmot & Ones, 2022).

Therefore, individuals high in Agreeableness would perceive and engage with relevant affordances linked to positivity and social behavior (see Figure 2). This interaction between individual and environment would be evidenced by embodied readiness to act upon such solicitations and affordances, for example, being expressed in interpersonal synchronization or coupling of behavior (Arellano-Véliz et al., 2024a).

Environments offering chances for positive social interactions, such as fostering positive social relationships and collaborative endeavors, are perceived as opportunities to be enacted (affordances). Agreeable individuals' skilled intentionality allows them to actively contribute to creating a positive social environment.

4.5. Conscientiousness

Conscientiousness can be seen as a dynamic self-organization process wherein an individual's tendencies to engage with specific affordances align with the trait's core characteristics of responsibility and orderliness (Costa & McCrae, 1992; DeYoung, 2015). Conscientiousness is defined in the literature as individual differences in the tendency or drive to order, responsibility to others, hard-working behavior, self-control, and following rules (Roberts et al., 2014). Their sensorimotor processes might be assembled in a way that promotes efficiency in the engagement with environmental stimuli related to goal pursuit, task-solving, planning, and work performance (Wilmot & Ones, 2019).

Conscientiousness is characterized by cognitive mechanisms that enable the soft assembly of task-specificity as well as the prioritization of non-immediate goals (DeYoung, 2015). Therefore, conscientious individuals are attuned to goal-oriented affordances within their environment, involving a selective perceptual focus on those relevant solicitations and affordances. Particularly, conscientious individuals' skilled intentionality is exhibited in an embodied readiness to actively engage with affordances related to long-term goal achievement and reduce distractibility, which would constitute their tendency toward an optimal grip (Hovhannisyan & Vervaeke, 2022). In our example, those situational affordances in the field of relevant affordances are represented by duty and intellect, which would suggest a synchronized engagement with multiple environmental affordances or solicitations to tend toward an optimal grip (Figure 2).

Overall, this section illustrated how personality traits involve dynamic processes of self-organization, wherein individuals engage with specific environmental affordances that align with their core characteristics. By attuning to relevant opportunities and challenges in their surroundings, individuals demonstrate a continuous interaction between their inherent traits and the situational demands they encounter. This dynamic interplay underscores the adaptive nature of personality, shaping how individuals navigate and respond to diverse contexts in pursuit of their goals and aspirations.

5. Discussion, Conclusions and Future Directions

As presented throughout this chapter, the integration of enactivism, embodiment, complex dynamical systems theory, and in a more specific account, the Skilled Intentionality Framework (SIF) offers a comprehensive approach to personality in situated environments. Traditionally understood as relatively stable and intrinsic characteristics influencing behavior, personality traits can be reconceptualized within a dynamic, enactive, and embodied framework. The enactive approach suggests that the patterns constituting behavior, and thus personality, emerge from the interaction between an individual and their environment through reciprocal causality (e.g., Thompson & Varela, 2001). This perspective implies that personality is not a static driver of behavior but an emergent property arising from these dynamic interactions. The embodied approach emphasizes the body's role in shaping experience and behavior, suggesting that personality traits are deeply intertwined with our physical makeup and movements (e.g., Koppensteiner, 2011; Jiang et al., 2023). Thus, bodily interactions with the environment are integral to the expression of personality, and it was emphasized through the embodied readiness toward action.

The complex systems approach implies viewing personality as part of a dynamic system where multiple interacting components give rise to emergent properties that cannot be fully understood by examining each component in isolation (e.g., Fajkowska, 2015; Nowak et al., 2020; Michaels et al., 2021). The phenomenon of functional synchronization is fundamental to understanding how system elements interact within the organism and with the environment. The indirect and complex relationship between system-level dynamics and individual personality traits (component elements of a complex adaptive system) can be mediated by factors such as situational constraints, feedback loops within dyadic interactions, and non-linear interactions. Therefore, the emergent patterns of behavior, affect, cognition, and desire (Wilt & Revelle, 2019) constitute stylistic differences that characterize distinct personality traits or dimensions.

The integrative perspective described was illustrated within the SIF and theory of affordances. From this perspective, personality expresses in a continuous engagement or attunement with environmental information and opportunities for action (affordances). This would constitute a reciprocal causality relationship that underscores the idea that personality and environment are intertwined in a dynamic process where each influences and is influenced by the other.

As shown in this last section, the application of the SIF (Rietveld & Kiverstein. 2014; Rietveld et al. 2018) to the Big Five personality traits offers a compelling perspective on how individuals engage with their environment. By viewing personality traits through the lens of individual-environment synchronization, and situated in a field of relevant affordances, we gain insight into how individuals differentially perceive and dynamically engage with the opportunities presented by their surroundings. This is fundamental for future research regarding metastable and multistable attunement in real-life and experimental contexts. Overall, this perspective emphasizes the importance of considering the dynamic interplay between individuals and their immediate environments, considering the process of skilled responsiveness to affordances as individuals strive to optimize their engagement with the world around them.

The integrative approach described can be extended to other psychological constructs (i.e., agency, attachment), and psychopathological conditions such as mood disorders and anxiety. This perspective can allow us to capture the mechanisms underlying behavior, cognition, and affect in ecological or experimental settings, either in social interactions or individual settings. Consequently, it becomes fundamental to study the embodied patterns and mechanisms of social interactions and intra-individual functioning. For example, at the social level, the micro-signals that people send to others through their movements, voice frequency, gaze, or breathing patterns. At the same time, how the information available or, affordances, are filtered and perceived to act upon; and how personality traits are expressed in such processes. At the individual level, it would be relevant to study how these embodied micro-signals or patterns are embedded in the emergence and persistence of mental disorders.

As we advance, it is crucial to mention the potential applications of this integrative framework in various domains. For instance, personalized interventions in clinical psychology can benefit from understanding how individual differences in personality traits influence engagement with specific affordances. And, tailoring therapeutic approaches to align with the dynamic patterns of interaction between individuals and their environments could enhance the effectiveness of treatments.

The methodological implications of the ideas covered in this chapter are multiple, but we will mention some of the most relevant. A complex, enactive, and embodied account can be applied through multimodal measurements to capture the dynamic patterns of behavior at different time scales (from milliseconds to patterns of behavior over longer periods such as days, weeks, months, or years) and diverse modalities. This approach involves collecting data from various modalities, including movement, neural activity, gaze, heart rate variability, and skin conductance, just to mention some. These embodied sources of information provide insights into the connections between bodily states and environmental interactions.

The integration of multiscale analysis considers the interaction of processes at different temporal and spatial scales. This creates novel opportunities for exploring how macro-level patterns of personality traits might emerge from micro-level interactions within individuals, emphasizing the importance of understanding personality from both bottom-up and top-down perspectives. Furthermore, it is fundamental to understand how the variability in personality traits (i.e., states) would affect sensorimotor processes, sensemaking, decision-making, and the coupling with the world through engagement with solicitations and affordances. In other words, the field of relevant affordances changes depending on how the perceived environment solicits activity—i.e., solicitations (Rietveld et al., 2018). Therefore, to capture such mechanisms, the micro-signals that express embodied readiness are a fundamental source of information.

In the methodological line, there is a fundamental challenge in experimental research which is how to make sense of chaotic behavior and Entropy when analyzing continuous data in the light of dynamic measures. A relevant insight in this regard would be not to provide a negative connotation to chaos and Entropy, but rather, understand that is a fundamental property of how complex systems behave. However, it is relevant to understand what are the "adaptive" parameters in which chaotic behavior is complex behavior and not random behavior. This should be a goal to study in experimental personality research, as it could provide a window to better understand the concept labeled as psychological Entropy (see Hirsh, 2012).

In the line of personality and environmental situatedness, we presented the DIAMONDS taxonomy of psychological situations (Rauthmann et al., 2014) as a way to illustrate how we could apply the Skilled Intentionality Framework (SIF) to situations within existing frameworks. While the authors of this taxonomy mention the concept of affordances in their theoretical background, these are not directly assessed, which is a notable limitation. Therefore, it is fundamental that future studies include direct measures that account for behavior in ecological or experimental settings to fully embrace an enactive, embodied, and complex dynamical approach. An alternative would be to either create or utilize existing behavioral protocols that correspond to each of the DIAMONDS dimensions. Importantly, such protocols should accurately capture relevant affordances observed in behavior or identified through embodied markers (e.g., physiological responses) that indicate how these affordances are enacted. Nevertheless, it is relevant to note that self-report measures are relevant to understanding reflective, subjective, and intersubjective processes, which are not disregarded. Instead, we aim for an integrative and complementary approach. This represents a necessary challenge for future studies.

In this sense, research should aim to test how engagement with relevant affordances occurs in both experimental and ecological situations, exploring the cognitive, embodied, and sensorimotor processes involved, as well as the role of individual differences and environmental constraints. To achieve this, multimodal studies are necessary as they allow the exploration of functional synchronization of different embodied modalities in the process of engaging with multiple affordances over time and across various situations.

Consequently, to further understand the mechanisms underpinning trait development and change, longitudinal studies encompassing comprehensive personality assessments (e.g., behavioral), physiological, and/or neuroimaging data are desirable. These studies are particularly important during critical periods such as the ages of 18 to 30 (as suggested by McCrae et al., 2020), where significant shifts in individual-environment coupling are likely to occur. Additionally, investigating personality, brain function, and sensorimotor development across the lifespan is crucial for a comprehensive understanding of the underlying dynamics (McCrae et al., 2020). This approach would enable the observation of how individuals perceive, act upon, and make sense of the affordances in their environments throughout their lifespan, accounting for individual differences.

Overall, the integration of multimodal measurements, experimental studies, ecological momentary assessments, longitudinal studies, and a focus on individual-environment interactions provides a robust foundation for future explorations in enactive, embodied, and dynamic personality science. As we continue to refine and expand this integrative framework, we move closer to a comprehensive understanding of the complex, dynamic nature of human personality and psychological science. This research has the potential to inform interventions, enhance diagnostic tools, and provide deeper insights into the interplay between personality, environment, and behavior. By embracing this multifaceted approach, we can explore new perspectives in the study of personality and contribute to theory and methodology development, more effective strategies for fostering psychological well-being and development.

Chapter 3

The Interacting Partner as the Immediate Environment: Personality, Interpersonal Dynamics and Bodily Synchronization

Published as:

Arellano-Véliz, N. A., Jeronimus, B. F., Kunnen, E. S., & A. Cox, R. F. A. (2024). The interacting partner as the immediate environment: Personality, interpersonal dynamics, and bodily synchronization. Journal of Personality, 92(1), 180-201. https://doi.org/10.1111/jopy.12828

Special Issue on Narrow and Broad Conceptualizations of Environmental Influences on Personality Editors: Rebekka Weidmann and William J. Chopik

Abstract

Objective: In social interactions, humans tend to naturally synchronize their body movements. We investigated interpersonal synchronization in conversations and examined its relationship with personality differences and post-interaction appraisals.

Method: In a 15-minute semi-structured conversation 56 previously-unfamiliar dyads introduced themselves, followed by self-disclosing and argumentative conversations, while their bodily movements were video-recorded in a standardized room (112 young adults, aged 18-33, mean = 20.54, SD = 2.74; 58% Dutch, 31% German, 11% other). Interpersonal bodily synchronization was estimated as (a) synchronization strength using Windowed Lagged Cross-Correlations and (b) Dynamic Organization (Determinism/Entropy/Laminarity/Mean Line) using Cross-Recurrence Quantification Analysis. Bodily synchronization was associated with differences in Agreeableness and Extraversion (IPIP-NEO-120) and post-conversational appraisals (affect/closeness/enjoyment) in mixed-effects models.

Results: Agreeable participants exhibited higher complexity in bodily synchronization dynamics (higher Entropy) than disagreeable individuals, who also reported more negative affect afterward. Interpersonal synchronization was stronger among extraverts than among introverts, and extraverts appraised conversations as more positive and enjoyable. Bodily synchronization strength and dynamic organization were related to the type of conversation (self-disclosing or argumentative).

Conclusion: Interpersonal dynamics were intimately connected to differences in Agreeableness and Extraversion, varied across situations, and these parameters affected how pleasant, close, and enjoyable each conversation felt.

Keywords: personality x personality interactions, dyadic interaction, complex dynamical systems, motion energy analysis, recurrence analysis, cross-recurrence quantification analysis, windowed lagged cross-correlations, synchrony

1. Introduction

Humans evolved to operate in interpersonal environments, and our most significant thoughts, feelings, and behaviors emerge in the context of social interactions (Buss, 2015; Galbusera et al., 2019). Social environments and interpersonal dynamics are therefore key to understanding individual differences (Larsen et al., 2020; Asendorf, 2020; Reddon et al., 2021). A fundamental mechanism in social interaction is the interpersonal synchronization and attunement of movement, speech, and physiological processes, largely driven by our unconscious (anoetic) awareness (Galbusera et al., 2019; Panksepp et al., 2012). Many subtle patterns of individual variability and covariation in interpersonal behavior unfold within the course of a single interaction (Sadler et al., 2015), and these nuances characterize human life (Sullivan, 1953). Accordingly, personality researchers have increasingly focused on environmental influences and their link to psychological processes (e.g., Lewin, 1946; Roche & Cain, 2021) and interpersonal functioning (Leary, 1957; Koban et al., 2019; Pincus et al., 2020).

The transition towards intra-individual and environmental conceptualizations of personality and trait dynamics requires theorists to connect processes across several time scales; from appraisal and affect (mere seconds), to conversations and emotions (minutes to hours), states of stress and mood (days to weeks), and the development of personality systems over years (Hopwood et al., 2018; Rauthmann & Shermann al., 2022), up to the diverse and complex patterns of age-based changes in social behavior along the lifespan (Siracusa et al., 2022). The Complex Dynamical System view provides a framework to understand and describe the evolution of behavioral systems over time (person, dyad, group, or personality system), and to study the interactions between systems and their environments (Fajkowska, 2015; Nowak et al., 2020; Kunnen, 2019); each individual can be understood as a dynamic system with unique architecture and dynamics.

This paper presents an experimental study on the interpersonal synchronization of body motion during a dyadic conversation between young adults. During the study, participants engaged in a 15-minute semi-structured conversation consisting of three parts: an introduction, self-disclosure, and an argumentative conversation. The study aimed to investigate whether differences in Agreeableness and Extraversion were linked to interpersonal synchronization, as well as the degree of positive or negative affect, interpersonal closeness, and enjoyment reported after the interaction. We were interested in dyadic (dis)similarity in the traits of Agreeableness and Extraversion as interacting partners who share low or high scores (i.e. are similar or "congruent/ complementary") or score rather differently on the trait dimension (i.e. are dissimilar or "discordant") because we assumed these dyads would synchronize differently.

The Agreeableness factor captures differences in sympathy and cooperation and shows concept overlap with the Communion axis in the interpersonal circumplex (see Pincus et al., 2020; Roche & Cain, 2021). Also, both Agreeableness and the Communion axes show substantial overlap with subclinical psychopathy, narcissism, and Machiavellianism personality factors (Klimstra et al., 2020). Extraversion was introduced by Jung (1921) to describe variation in orientation toward the world and the factor captures individual variability and differences in (a) positive affect and (b) interpersonal engagement (sociability) with both gregariousness/affiliative and dominance/agency components; Extraversion shows concept overlap with the Agency axis in the interpersonal circumplex and Gray's (1971) motivational "behavioral approach system". See Depue and colleagues (1999) and Larsen and colleagues (2020).

Synchronization was operationalized as synchronization strength (analyzed with Windowed Lagged Cross-Correlations, WLCC) and dynamic organizatio,n (analyzed with Cross-Recurrence Quantification Analysis, CRQA; see Table 1 for variables and definitions). We expected that (dis)similarity in Agreeableness and Extraversion would be associated with differences in synchronization across the three parts of the conversation. Second, we expected that synchronization would be associated with affect valence, interpersonal closeness, and enjoyment. Below we first introduce the concept of interpersonal synchronization in more detail, as well as its theoretical and empirical links with personality. Subsequently, we introduce the basic theories on personality dynamics and environmental approaches to outline the promise of studying interpersonal interactions within the complex dynamical systems framework.

1.1. Interpersonal Synchronization

Spontaneous interpersonal synchronization requires several system elements and dynamics such as body movement to become coupled over time (Tschacher et al., 2014). Social interactions unfold via shared behavioral, cognitive, emotional, and physiological processes and this system requires coordination or synchronization over time (Smith, 2018), such as is evident in natural behaviors like parenting (Buss, 2015) or a performing orchestra (Levitin et al., 2018). The conceptualization of interpersonal synchronization of behavior differs across research fields but generally includes time-dependent matching behaviors, the coordination of movements, and/or the dynamic interaction between individuals (e.g., Bernieri, 1988; Cox et al., 2016; Delaherche et al., 2012; Launay et al., 2013; Hu et al., 2022; Siracusa et al., 2022).

An early definition of interpersonal synchronization describes the spontaneous coordination of body motion as well as linguistic behavior between individuals when they are interacting (Bernieri, 1988; Cornejo et al., 2017) or the "degree to which the behaviors in an interaction are non-random, patterned or synchronized in both timing and form" (Bernieri & Rosenthal, 1991, p.403). Synchronization can emerge in physiological processes like heart rate (Konvalinka et al., 2011; Pérez et al., 2021), language (Fusaroli, Bahmari & Olsen et al., 2012), or neural processes (Astolfi et al., 2010). Based on these classical definitions, a review study (Cornejo et al., 2017) specified that interpersonal synchronization requires some attributes, namely: (a) That synchronization is a social phenomenon between two or more individuals (Bernieri et al., 1988; Schmidt & Richardson, 2008; Marsh et al., 2009), (b) implicates co-presence (e.g., face-to-face interaction, see Bernieri & Rosenthal, 1991), that (c) synchronization emerges in a short time-frame, and (d) is spontaneous (i.e., it is pre-reflective, e.g., Davis, 2016). Other forms of synchronization and time scales are possible and have been observed, like intra-personal synchronization (e.g., between limbs, Galbusera et al., 2019) or changes in social dynamics with age (Siracusa et al., 2022).

One way to study synchronization across different levels of human activity is the complex dynamical system framework, which has been used to study systems from neural processes to body movement and social pattern formation (e.g., Richardson et al., 2014). One key theory in complexity studies is that lower-level processes can give rise to the emergence of higher-order "functional units" in a coordinated multilayer system (Kunnen et al., 2019; Nowak et al., 2017). In the context of dyadic interactions, individuals must work as one unified system to derive and maintain systemic stability and coupling to sustain communication via flexible co-regulation of behavior, which promotes more stable attractor states (Galbusera et al., 2019; Mischel & Shoda, 1995; Shoda et al., 2002; Koban et al., 2019).

1.2. Quantification of Interpersonal Synchronization Employing Time-Series Analysis

There are several approaches to measuring and operationalizing interpersonal synchronization based on time-series analysis (for systematic reviews see Mogan et al.,2017; Wiltshire et al., 2020; or Ayache et al., 2021; and Schoenherr et al. (2019a) or Hu et al. (2022) for review articles). Common modalities on which interpersonal synchronization is operationalized and measured are body motions using video analysis (e.g., motion energy analysis, Ramseyer & Tschacher 2011), motion capture (e.g., optical motion capture systems), and psychobiological (e.g., heart-rate), neurophysiological measurements (Cornejo et al., 2017), which are among a variety of modalities.

In this study, we utilized two time series techniques. First, a common approach to assess synchronization strength uses the grand average of cross-correlations between two time-series, which can be determined with Windowed Lagged Cross-Correlations (WLCC, e.g., Kleinbub & Ramseyer, 2021). Second, Cross-Recurrence Quantification Analysis (CRQA) is a nonlinear time series approach to address the dynamic organization of synchronization, particularly, estimating coupling dynamics between two time series (Wallot et al., 2018; Xu et al., 2020). In this study, we focused on coupling dynamics expressed by Determinism, Entropy, Laminarity, and Mean Line. The coupling between the two time series (or systems) can be visualized by matching points in a Cross-recurrence plot (see Figure 2). These measures and their definitions are provided in Table 1 and the method section and we combined both techniques (WLCC and CRQA) in our study to benefit from their complementary information on dyadic body synchronization.

1.3. Personality, Synchronization, and the Interacting Partner as the Immediate Environment

The interacting partner in a dyad is henceforth understood as the psychological environment in which each individual is engaged, and where individual differences surface (Sullivan, 1953; Leary, 1957; Asendorf, 2020; Roche & Cain, 2021). Individuals tend to synchronize more readily when they possess similar features (similarity) which could be perceived from body motion information associated with personality traits (e.g., Koppensteiner, 2013), as behavioral states are theorized to synchronize more readily when smaller system adjustments are required to reach a dyadic attractor state with systemic stability (Nowak et al., 2020; Rivera et al., 2010), which connects dyadic synchronization to improved person-environment fit (e.g., Van Vianen, 2018; Vleugels et al., 2022).

We argue that dyads with dissimilar personalities must accommodate more, which requires them to temporarily leave their personal baseline and attractor states to synchronize, which takes more time and resources (low person-situation fit and high costs), which is expected to make interactions more unpleasant or unattractive (Vleugels et al., 2022). Both interactants may need to adjust, or a synchronized state may not be achieved. Previous work suggests that mutual influences in behavior, affect, and cognitions may be too weak to achieve synchronization or too strong such that interactants constrain or restrict their interacting partners in excess (Nowak et al., 2020). Therefore, a moderate degree of mutual influence would optimize the interpersonal synchronization of each individual during the interaction. Although most humans aim to attain a person-environment fit, we differ in motivation, ability, and investment of resources to achieve social fit (Larsen et al., 2020; Rauthmann, 2021). Hence, some people may be able to facilitate synchronization using Agreeable empathy or Extraverted sociability, thus in some dyads composed of agreeable/disagreeable and extraverted/introverted individuals (everything else equal, such as motivation). These premises can be examined during first interactions between individuals, especially if we consider each personality trait as an indicator of (dis)similarity, quantify the degree of bodily synchronization, and ask participants to appraise the interactions in which they are involved (Nowak et al., 2020).

A systematic literature review by Ayache and colleagues (2021) on interpersonal synchronization across different experimental settings suggested that argumentative settings decrease synchronization between participants but that affective settings had no effect on synchronization (using cross-correlation analysis and CRQA, see Paxton & Dale, 2013, 2017). Other studies suggested more synchronization both during competitive and affiliative conversations (using WLCC on motion energy of full body movements, see Tschacher et al., 2014, 2018). A third body of evidence suggests that the co-regulation of dynamic sympathetic and behavioral rhythms is a mechanism to promote interpersonal attraction (Zeevi et al., 2022). Few studies on interpersonal synchronization have been conducted in the personality domain, but the study by Tschacher et al. (2018) with 84 dyads, suggested that more Openness to experience and a less narcissistic interpersonal style (associated with Agreeableness) were linked to (longer) interpersonal synchronization.

Pioneering personality studies on dyadic interactions reported that Agreeableness (A) and Extraversion (E) shaped interpersonal interactions most directly, while the effects of Conscientiousness, Neuroticism, and Openness were less clear (e.g., Cuperman & Ickes, 2009; Lakey et al., 2021). These results align with interpersonal theory in which differences in Communion and Agency are key to describing how individuals interact, which are often described as rotations of the Agreeableness and Extraversion trait space (Larsen et al., 2020; Pincus et al., 2020, p.5). Based on these premises we focused our paper and experimental design on differences in Agreeableness and Extraversion, although we acknowledge that other personality dimensions (can) play a crucial role as well.

1.4. The present study

In this paper, we investigate interpersonal synchronization in semi-structured conversations and examine the link between personality differences, synchronization strength and dynamic organization, and post-interaction appraisals (affect/interpersonal closeness/enjoyment) using mixed-effects models. Specifically, we focus on Agreeableness and Extraversion, which have been previously linked to interpersonal dynamics and synchronization in research (Cuperman & Ickes, 2009; Koban et al., 2019; Toc et al., 2016). Interpersonal and complementarity theories suggest that highly agreeable individuals elicit friendly and agreeable behavior from others (sameness), while more extraverted or dominant individuals often elicit more submissive behavior from their interaction partner (opposites; see Sadler et al., 2015).

We hypothesized (H1a) that dyads composed of highly agreeable individuals (similar dyads) would show more body motion synchronization, appraise the conversation (more) positively, and achieve more systemic coupling than dyads with disagreeable participants do. Disagreeable dyads would exhibit poor synchronization and more negative post-interaction appraisals (H1b). For the mixed or "dissimilar" Agreeableness dyads we hypothesized (H1c) a moderate degree of interpersonal synchronization in comparison to the other groups, and more negatively appraised interactions (Cuperman & Ickes, 2009).

Extraversion-similar dyads were expected (H2a/H2b) to synchronize more and appraise the conversation and peer more positively than in dissimilar dyads, for whom we expected moderate synchronization and more negative appraisals in terms of affect, interpersonal closeness, and enjoyment.

Third, we explored whether dyadic synchronization of body motion differed across the three conversation types (self-introduction/self-disclosure/argumentative) and whether Agreeableness and/or Extraversion scores moderated such synchronization. Finally, we expected that (H3) interpersonal synchronization would differ between the self-disclosure and argumentative conversations, when compared to the self-introduction, but refrained from specific hypotheses as we aimed to explore dyadic configurations.

2. Method

2.1 Participants

Students of the University of Groningen were rewarded with European Credit Transfer and Accumulation System (ECTS) credits. Of the 300 screened students 112 fit our criteria on personality scores (≥0.5 SD from sample mean) and agreed to attend a laboratory session after being invited (82 females and 30 men), which yielded 56 same-gender dyads (age range 18-33, mean = 20.54, SD = 2.74) from diverse backgrounds (58% Dutch, 31% German, 11% other)[1]. Originally, we combined participants on dyads focusing on their (dis)similarity in Extraversion and Agreeableness scores, being either "low" (-0.50 SD) or "high" (+0.50 SD) scorers compared to the sample average (e.g., Li et al., 2020). Our models used the full sample of 112 participants as we model the personality traits of interest continuously while preserving the dyadic structure in a parsimonious way, as we explain below.

1 Note: We recognize that the modest sample size may limit our results compared to typical studies in personality, but we rely on standardized tasks and intensive time-series, and provide statistical power estimates. Multiple experimental studies in the field of interpersonal synchronization employing time-series methods on modest samples provided relevant results even with 19 dyads (Konvalinka et al., 2011), 27 dyads (Perez et al., 2021), 30 dyads (Tomassini et al., 2022), 70 dyads (Ramseyer & Tschacher, 2011; 2014), or 84 dyads (Tschacher et al., 2018), as outlined in systematic reviews by Wiltshire and colleagues (2020) or Ayache and colleagues (2021).

2.2. Self-Report Questionnaires and Protocols

2.2.1. International Personality Inventory Pool - 120 (IPIP-NEO-120)

Personality traits were measured online using the IPIP-NEO-120 (Johnson, 2014) on the Qualtrics platform, approximately 10 days before the laboratory study was conducted. The IPIP-NEO-120 comprises 120 items that measure the big five personality traits Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness, and their thirty facets (5*6).[2] The psychometric properties reported by the author (Johnson, 2014) were consistent with the psychometric properties of the NEO-PI-R scales (Costa & McCrae, 2008), which indicates reliable and valid scales. The IPIP-NEO-120 and NEO-PI-R scales showed high correlations (Neuroticism 0.87; Extraversion 0.85; Openness to Experience 0.84; Agreeableness 0.76; and Conscientiousness 0.80 (all $p<.01$); $N = 501$, Johnson, 2014), and the IPIP-NEO-120 showed a good internal consistency (Cronbach's alpha of 0.88, 0.84, 0.85, 0.81, and 0.84, respectively). The IPIP-NEO-120 has public domain availability and cross-cultural robustness to allow for an international sample.

2.2.2. International Positive and Negative Affect Schedule Short Form (I-PANAS-SF)

The I-PANAS-SF (Thompson, 2007) was used to measure the positive and negative affect states after the interaction. The I-PANAS-SF consists of 10 emotion adjectives of which half measure positive affect (determined, attentive, alert, inspired, active) and half negative affect (afraid, nervous, upset, ashamed, hostile), each item rated on a scale from 1 (very slightly) to 5 (extremely). Positive and negative affect (PA/NA) scales were created by adding the item scores. The psychometric properties of this 10-item PANAS were comparable to the original 20-item questionnaire (PA $r = .92$, NA $r = .95$, both $p < 0.01$; Thompson, 2007). The I-PANAS-SF exhibits adequate test-retest reliability ($N = 143$, $r = .84$ both PA/NA, $p < 0.01$), and good internal consistency with Cronbach's alpha from 0.72 to 0.78 (Thompson, 2007), similar to the original 20-item version (Watson et al., 1988).

2.2.3. Perception of the interaction

After the dyadic interaction, to examine how the participants appraised their interaction, participants were asked to complete a modified version of the Perception of the Interaction questionnaire (used by Cuperman & Ickes, 2009). In this paper, we only report how participants enjoyed their interaction, the scores go from 1 ("not at all") to 5 ("very much").

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2 see https://ipip.ori.org/30FacetNEO-PI-RItems.htm

2.2.4. Interpersonal closeness

The other-in-the-self scale (Aron et al., 1992) invites participants to describe their interaction and conversation partner graphically by choosing one out of 7 Venn diagrams with increasing overlap, anchored as “not at all close” (score 1) to “extremely close” (7), see example in Supplementary Figure S1.

2.2.5. Self-disclosure

The self-disclosure paradigm is an experimental protocol in which both participants of a dyad ask and answer several questions (Aron et al., 2017). The objective of the protocol is to create closeness in an experimental context. The original version is composed of three sections with 12 questions each, and the task typically takes 45 minutes. We shortened the protocol to three sets of three questions each, for which we took approximately five minutes in our study. The sets had increasingly personal questions such as “what would constitute a “perfect” day for you?” (see example items in Supplement S1).

2.3. Procedure

Participants were invited to the laboratory and received a heart rate transmitter belt (results not part of this paper) before completing their interpersonal task instructions, informed consent, and affective state schedule. The participants were instructed to clip a microphone on their clothes and to stand in front of each other on a board for measuring postural control (not part of this paper) in a fixed position at 1.5 meters (m) distance. A camera was situated by one of the sides at approximately 4.5m, recording the interaction from a sagittal perspective. The conversation task consisted of a 15-minute semi-structured interaction divided into three parts (5 minutes each); (1) an introduction of oneself; (2) self-disclosure topics; and (3) an argument or debate. Each part is now outlined in more detail.

First, participants were asked to introduce themselves briefly to their conversation partner for 5 minutes in an unstructured way. Examples of topics were provided in case guidance was needed. The subsequent “self-disclosure” phase required participants to ask questions to each other using a modified version of Aron’s (1997) self-disclosure paradigm. Participants selected the questions they wanted to talk about for five minutes, and the requirement was that both interactants had to answer each question. They were instructed to freely decide what they wanted to share with their partner. During the argumentative phase, participants chose a conversational topic from a pool of approximately 20, and adopted opposite sides of the argument (pro/against) on topics such as “Are dating apps a good platform for meeting a romantic partner?” (example item). Dyads discussed as many topics as five minutes allowed, the time was delimited by an alarm, but the participants could finish their conversation before moving to the next phase. After the interaction, every participant completed the affective state, interpersonal closeness, and perception of the interaction questionnaires. All the data streams were recorded using Lab Streaming Layer software (Kothe et al., 2019).[3]

2.4. Quantification and Statistical Analysis

2.4.1. Operationalization of Interpersonal Synchronization

To quantify synchronization strength, we used a linear time-series technique (WLCC), whereas the dynamic organization of the synchronization was analyzed with a nonlinear time-series technique (CRQA). Linear time-series techniques based on cross-correlations are limited in assessing the coupled dynamics of complex and nonstationary systems, such as biological adaptive systems, for instance when extracting time-series means from a system with multiple points of stability or without a persistent central point (Tolson et al., 2020). CRQA, as a nonlinear time-series technique, is more robust, with few data assumptions, and provides additional information about the dynamic organization of the coupled behavior of the systems under investigation (Shockley et al., 2002). CRQA quantifies patterns of recurrent behaviors emerging over time in two data streams. We combined CRQA with WLCC to quantify various aspects of interpersonal synchronization in motion energy time-series (Kleinbub & Ramseyer, 2020). An overview of the study variables and statistics is provided in Table 1.

2.4.2. Motion Energy Analysis (MEA)

The Motion Energy Analysis Software (version 4.b. For Windows, Ramseyer, 2018; 2020) was employed to calculate the amount of movement of each person based on the desired target area frame by frame, in this case, the full human body (see Figure 1). This method provides the amount of change among pixels, quantifying the movement of each individual (Ramseyer, 2019). From video recordings of 32 frames per second (fps), we extracted the raw data (approximately 28.800 data points average per person), each a summary of one time-series for each subject (two for each dyad). Then, nonverbal synchronization was assessed using both linear and nonlinear time-series techniques on the three specific segments or types of interactions (self-introduction, self-disclosure, argument). First, a Windowed Lagged Cross-Correlation (WLCC) analysis was performed using the R package rMEA (Kleinbub & Ramseyer, 2020) in the R studio environment (R core team, 2022). Subsequently, Cross-Recurrence Quantification Analysis (CRQA) was conducted, to examine across-time scale attunement.

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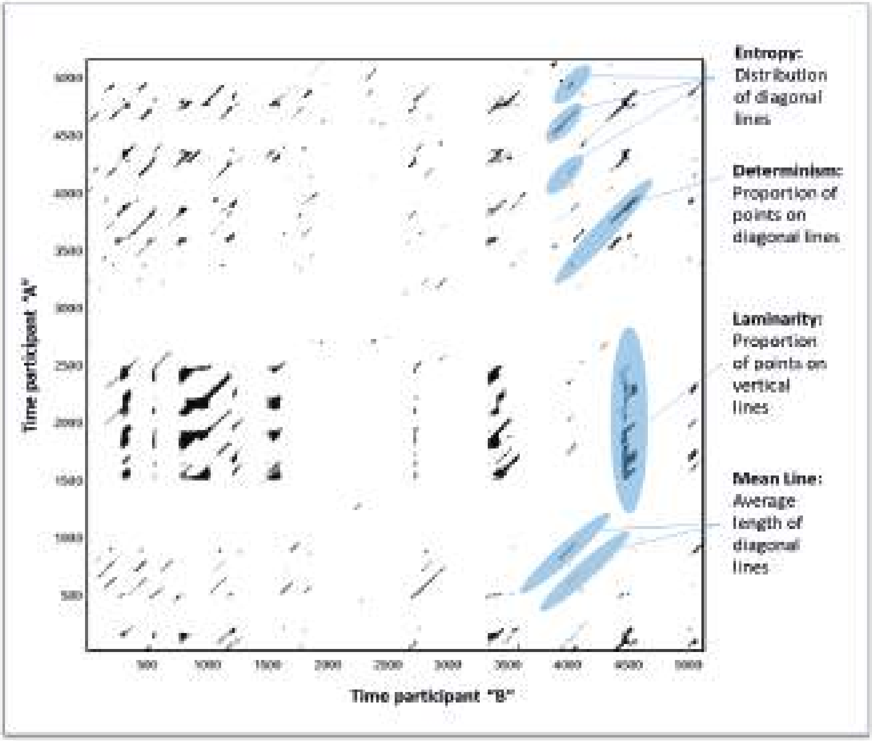
3 *https://doi.org/10.17605/OSF.IO/XQGSA*

Figure 1. Example of Motion Energy Analysis performed on the MEA software

Note: The figure shows an example of the time series generation using the MEA software in one of the video recordings of this study (Ramseyer, 2018; 2020).

Figure 2. Cross-recurrence plot representation of one of the dyads during the Self-Disclosure task



Note: Cross-recurrence plot of body motion during the self-disclosing task. See Table 1 for definitions. The black points represent the time points where recurrence is identified. They represent temporal coordinates where the trajectories of both time-series are close enough according to the defined parameters (Coco et al., 2017). The parameters employed to perform the CRQA were: lag or delay = 40, embedding dimension or dim = 7, a fixed recurrence rate was set at 2%.

Table 1. Operationalization of interpersonal synchronization and statistics for body motion variability (Motion Energy time-series) (*)

Strategy Step 1: **Time-series analyses**	**Strength of Synchronization - Linear technique**		
	Technique Description	**Windowed and Lagged Cross Correlations (WLCC):** Strength of synchronization between two time-series by means of their cross-correlation between time windows. Results in a single outcome measure.[1-2] WLCC quantifies synchronization strength between the participants in the dyad.[1]	
	Variable	**Definition**	**Interpretation**
	Strength - **Interpersonal Synchronization Grand Average**	The cross-correlations in the time-series matrix are Fisher's-Z converted and aggregated to an output score representing the strength of interpersonal synchronization. This is a grand average of the correlation between time-series.[2]	Indicates the value of the windowed lagged cross-correlations, which can be positive (simultaneous) or negative (one accelerates and the other decelerates body motion). This phenomenon can be interpreted as co-regulation.[2]
		Dynamic Organization of Synchronization - Nonlinear technique	
	Technique Description	***Cross-Recurrence Quantification Analysis (CRQA)***: Quantifies recurring patterns across all possible timescales in the shared reconstructed phase space. Results in several outcome measures reflect different aspects of the coupled dynamics. Quantifies the dynamic organization of the interaction in the dyad.[1]	
	Variable	**Definition**	**Interpretation**
	Determinism (DET)	Proportion of recurrent points along diagonal lines in the cross-recurrence plot (CRP). A diagonal line is a collection of (minimally two) subsequent recurrences, indicating that the trajectories of the two systems follow each other in reconstructed phase space. Diagonal lines can have various lengths representing shorter or longer episodes of recurrence (see ML).[6-7]	It gives a representation of the regularity and predictability of coupling between the two signals.[6-8] Perfectly coupled systems would exhibit a value close to 1, and less coupled systems have lower values. The higher the DET, the stronger the coupling of the systems.[6-7]

Table 1. Operationalization of interpersonal synchronization and statistics for body motion variability (Motion Energy time-series) (*) (continued)

	Entropy (ENT)	Shannon Entropy of the distribution of the length of diagonal lines in the CRP. Estimates the complexity of the system's deterministic structures.[7] Indicates the variety of patterns by which the two time-series are coupled, as well as the type of paths that the systems visit in the reconstructed state space.[6]	Lower values of ENT will indicate a greater likelihood (highly repeatable, regular, and more rigid paths), while higher ENT values indicate a lower probability, which can indicate both higher irregularity and also more ***complexity*** and flexibility in the trajectories visited for the systems.[4-6]
	Laminarity (LAM)	Proportion of recurrent points forming vertical lines in the CRP, which provides a quantification of the occurrence of laminar states in the system (intermittency).[7] Laminar structures represent episodes in which the systems capture each other in a particular (point attractor) state.[8-9]	High values of LAM represent more laminar states, it can be referred to as rigidity, indicating that the systems remain in a certain shared state (e.g., a fixed dyadic state). Lower values of LAM ate linked to more flexibility in the dynamics of the system because of its variability.[8-9]
	Mean Line Length (ML)	Mean length of all the diagonal lines in the CRP.[4] ML indicates the average period of coupling of the signals. The longer the average line length, the longer on average the two systems are coupled in the reconstructed phase space.[6]	Estimates the dynamical stability of the system. Larger values indicate stronger, longer (on average), and more stable coupling or synchronization of the two systems.[6]
Expectations	Similar dyads in Extraversion and high Agreeableness would exhibit a higher ***Strength*** of interpersonal synchronization; and stronger dyadic coupling expressed by higher DET, higher ML, lower ENT, and lower LAM. Dissimilar dyads in Extraversion and Agreeable scores would exhibit moderate strength and coupling compared to the previous ones, while low agreeable or "disagreeable" dyads would exhibit low/weak coupling.		
Step 2: Statistical Procedures	<u>WLCC and CRQA:</u>. a. Descriptive statistics for linear and nonlinear techniques. b. Multilevel mixed-effects models testing personality differences in their synchronization (WLCC) of body motion, and dynamic organization or coupling of body motion (CRQA).[10] <u>Post dyadic interaction measures:</u> c. Multilevel models testing the effect of WLCC and CRQA variables on post-interaction measurements.[11]		

(*) Note. Analysis for body motion comprises CRQA and WLCC. References. 1 Schoenherr et al. (2019a). 2 Ramseyer (2020). 3 Xu et al. (2020). 4Wallot & Leonardi (2018). 6 McCamley et al. (2017). 7 Curtin et al. (2017). 8 Konvalinka et al (2011). 9 Dimitriev et al., (2020). 10 Lumsden et al. (2014). 11 Tschacher et al. (2018).

2.4.3. Windowed Lagged Cross-Correlations to measure Motion Energy Synchronization

The rMEA package relies on the windowed and lagged cross-correlation approach using an algorithm with lag analysis to measure nonverbal or movement synchronization (Kleinbub & Ramseyer, 2020). In WLCC the raw time-series of Motion Energy were pre-processed into (a) average scores over time windows of 0.5 seconds (smoothing) and (b) standardized using the SD (rescaled) to obtain relative movement scores to be better able to compare and interpret differences in motion. Third, the data streams were cleaned in order to remove artifacts in the signal and possible outliers given involuntary changes (such as changes in lighting), during cleaning all missing data and values >10 times the SD of each motion energy time-series were removed following Kleinbub & Ramseyer (2020). The subject with the highest score was always “Subject 1/A” to help interpret leader-follower asymmetries in dissimilar dyads.

WLCC helps to identify movement or nonverbal synchronization over time (Bernieri & Rosenthal, 1991; Schoenherr et al., 2019b), and is used to measure the dynamic association between short-time segments (lags) of two paired time-series (Boker et al., 2002). Differences in the correlation between different segments of time of subjects A and B are tested, after which the time-series of subject B are shifted, and the procedure is repeated, throughout the time-series, until all time lags have been compared. Ultimately, the WLCC identifies the exact time points at which the behavior of subject A is significantly correlated with the simultaneous (or time-lagged) behavior of subject B (Schoenherr et al., 2019b), and we calculated the grand average of synchronization between interactants, by transforming the values to Fisher’s Z. The parameters employed were lag = 5 seconds, which means that the analysis captures how the two time series influence each other with a delay of up to 5 seconds. Window = 30-second window means that each correlation calculation is based on a 30-second segment of the data. This window size provides a balance between capturing enough data points for reliable correlation estimates and maintaining temporal resolution. Increment = 10 seconds, which means that the sliding window shifts by 10 seconds each time, creating overlapping windows. This overlap ensures that the analysis captures smooth and continuous changes in the correlation over time, rather than abrupt transitions (for detailed information consult Kleinbub & Ramseyer, 2020).

2.4.4. Cross-Recurrence Quantification Analysis for Assessing Dynamic Organization

CRQA was performed on the motion energy time-series of the participants. Recurrence-based analyses focus on identifying recurring patterns within systems across various time-scales (see e.g., Marwan et al., 2007; Wallot & Leonardi, 2018; Wijnants et al., 2012). CRQA is the bivariate version of recurrence analysis, providing metrics of attunement and coordination by quantifying recurrent patterns in coupled dyadic systems (Shockley et al., 2002). The cross-recurrence plot (see Figure 2) is the primary tool for visualizing and quantifying these recurring patterns within a reconstructed phase space. A recurrence or 'match' in this context refers to the re-occurrence of a point within the reconstructed phase space, signifying that the dyadic system has returned to a previous state (Marwan et al., 2007). This recurrence reflects the self-organizing dynamics of the interaction between participants. However, this method does not capture directly observable behaviors like a specific gesture or movement (this can be achieved through categorical CRQA, see Wallot & Leonardi, 2018). Instead, it involves embedding the time-series data into a higher-dimensional phase space to model the underlying dynamic states. The recurrence identified represents a return to a prior dynamic state within this abstract mathematical model, rather than a specific physical action. This abstraction allows us to capture the complex temporal dynamics of synchronization that might not be immediately visible in observable behavior but are crucial for capturing the dynamics of dyadic coupling.

Participants influence each other concurrently, possibly with a time delay, and for longer and shorter durations. CRQA is able to identify and quantify the resulting behavioral patterns. This is a key difference with WLCC: CRQA provides a more extensive account of the interaction by quantifying recurrent patterns across the entire interaction, spanning from immediately to the full duration of the interaction. We included four of the possible recurrence measures in the statistical analyses: Determinism (DET), Entropy (ENT), Laminarity (LAM), and Mean Line Length (ML). Each measure quantifies either the extent or duration of recurrent patterns (lines) of at least two recurrent points in the cross-recurrence plot (see definitions in Table 1). These CRQA measures complement the estimate of synchronization from the WLCC.

The same preprocessing steps of WLCC (smoothing, rescaling, cleaning) were applied before conducting CRQA. The time-series were down sampled by a factor of two to reduce computational demands. The parameters for the phase-space reconstruction (lag and dim) were set to the following values: lag = 40 and embedding dimension or dim = 7, following steps described in for instance Wijnants and colleagues (2012) and Wallot & Leonardi (2018). Instead of a pre-specified radius, we used a fixed recurrence rate of 2% for all dyads to facilitate the comparison of the CRQA measures across conditions (e.g., Konvalinka et al., 2011; Wijnants et al., 2009).

2.5. Power and Effect Size

Some effect size indices commonly employed to report results in psychology are: coefficient of determination (R^2), Cohen's d or Cohen's f^2, correlations (r), and partial regression coefficients (β). We understand the coefficient of determination (R^2) as weak if they were between 0.02 and 0.13; moderate between 0.13 and 0.26 and substantial if they are larger than 0.26 (Cohen, 1988); correlations (r) and beta's (β) as small if they were between 0.10 and 0.19, moderate between 0.20 and 0.29, and large from 0.30, based on effect sizes commonly found in social psychology (Peterson & Brown, 2005; Richard et al., 2003). For an effect size of around r = .20 (the average effect in personality and social psychology, Richard et al., 2003), studies need approximately 150 participants to reduce estimation error in correlations (Schönbrodt & Perugini, 2013) but note this estimate is conservative in our study which draws additional power from the 28.800 consecutive data points per person (on average) in time series (see p.14).

We follow Cohen's (1988) guidelines and define $f^2 \geq 0.02$ as small, $f^2 \geq 0.15$ as medium, and $f^2 \geq 0.35$ as large effects. Cohen's can be employed both to express global effect magnitude in the context of linear regression models and for single fixed effects in the context of multiple estimates (local effect size), which is recommended for hierarchical data and mixed-effects models with continuous predictors and response variables (e.g., Selya et al., 2012). Cohen's f^2 is calculated as the ratio of the explained variance (R^2) in the dependent variable due to the fixed effect to the residual variance, and can be also extracted from the t values and degrees of freedom of the error estimate of each fixed effect, as we calculated local effect sizes (Ben-Shachar, 2020). Based on our design, with a sample size of 112, given a Cohen's f^2 of 0.35 (a large effect size), and a power of 0.88, our study was expected to detect moderate to large global effects with a degree of accuracy of 88% at a significance level of 0.01 (following the recommended procedure for mixed-effects models by Selya et al., 2012).[1] This power analysis indicates that the sample size was adequate to detect the effects of interest with a reasonable level of confidence. We controlled the False Discovery Rate by employing the Benjamini-Hochberg (1995) procedure in all the models which is a sequentially modified Bonferroni correction to adjust for alpha inflation due to multiple hypothesis testing (with the stats R package; R core team, 2022).[2]

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1 Calculated with the 'pwr' R package (Champely, 2022).

2 False discovery rates (FDR) refer to the likelihood of incorrectly rejecting a hypothesis when testing multiple hypotheses. The Benjamini-Hochberg is a step-up FDR-controlling method, where hypotheses are ordered based on their p-values (from smallest to largest), and then accepted or rejected based on the number of tests and the rank of each hypothesis (Benjamini & Hochberg, 1995).

3. Results

We operationalized interpersonal synchronization as measures of strength and the Determinism/Entropy/Mean-Line/Laminarity of the dynamic organization, resulting in five models to examine synchronization. Below we examine the role of Agreeableness and Extraversion in interpersonal synchronization (strength and dynamic coupling, respectively). Significant correlations are described for each variable of interest in this study and also for all Big Five personality traits in Table S1, but we focus our results on differences in Agreeableness and Extraversion.

3.1. Descriptive Statistics

To test synchronization strength across our sample and the three types of interaction, Windowed Lagged Cross-Correlations (WLCC) between Motion Energy Analysis (MEA) were calculated for each type of interaction (self-introduction/self-disclosure/argumentative), which lasted approximately five minutes each (168 total interactions: 3 conditions * 56 dyads). We did not use absolute values of the interpersonal synchronization grand average in order to capture the sign of the observed synchronization, positive (simultaneous) or negative (turn-taking). WLCC models indicated a grand average of -0.02 ($SD = 0.03$) on synchronization across all dyads during the total 15 minutes of interaction (3*5 min). A fixed-effects analysis of variance (ANOVA) identified no gender differences in synchronization ($F(1,54) = 1.91$, $p > 0.17$). The observed values of the CRQA variables are: Determinism (mean = 0.93, SD = 0.03), Entropy (mean = 2.32, SD = 0.21), Laminarity (mean = 0.97, SD = 0.01), Mean Line (5.94, SD = 1.20). Descriptive statistics for all the variables of interest are expressed in Table 2.

3.2. Strength of Interpersonal Synchronization: WLCC of Body Motion

To estimate the association between personality traits and interpersonal synchronization, a Maximum Likelihood (ML) linear mixed-effects model was fit in R (package lme4; Bates et al., 2015), with participant scores nested within the dyadic structure (a hierarchical two-level organization). The evaluation of significance was calculated employing Satterthwaite's method for computing the approximate degrees of freedom for t distributions (R package lmer4, Bates et al., 2015).

Synchronization strength was the response variable (grand average WLCC), the model included fixed effects of Agreeableness scores (Agreeableness A * Agreeableness B) and Extraversion scores (Extraversion A * Extraversion B), and the type of conversation (a categorical variable: introduction, self-disclosure and argumentative, where the introduction was the baseline condition).[3] The model included a random intercept at the dyadic level. All continuous predictor variables were centered and rescaled (using SD) in order to compute the models without convergence issues (equations are provided in Supplement S2). To facilitate the interpretation of the results, the participant with the highest score within the dyad corresponds to "A1" or "E1" and the lowest to "A2" or "E2". The p-values were corrected by means of the False Discovery Rate procedure. We expected that dyads with high Agreeableness scores and dyads with similar scores in Extraversion would show higher synchronization strength. Dyads with dissimilar scores (on Agreeableness/Extraversion), in contrast, were expected to exhibit moderate strength in comparison to the previous dyads, versus low strength among low Agreeable dyads. In Table S2, we present the results with the corrected p-values.

The model was statistically significant (estimate = -0.03, [-0.04 to -0.02], SE = 0.004 $p < 0.001$) and the total variance explained by the full model (fixed and random effects combined) was $R^2 = 0.47$ (i.e. substantial, Cohen, 1998). About 38% of the variance of synchronization strength was explained by the particular dyad to which each participant belongs (Intraclass correlation [ICC], Kenny et al., 2006), indicating that the variation between dyads is a relevant factor to consider when analyzing the relationship between predictors and our dependent variable. This full model appears reasonably powered to explain synchronization differences among the 56 dyads (112 participants) as the observed power is 89.7% to detect a global effect size of Cohen's $f^2 = 0.90$ (at $p<.001$), being indicative of the explained variance by the fixed and random effects of the full model, which will differ from local effect sizes of fixed effects (see Selya et al., 2012 for details).[4] For individual estimates, we calculated local effect sizes as guidance, which can be more informative.

Extraversion scores of both conversation partners predicted interpersonal synchronization, especially during the self-disclosure task (estimate = -0.02 [-0.03 to -0.01], SE = 0.01, $p = 0.03$). The local effect size (in the context of the full model) of E.A*E.B*Self-Disclosure was of a small magnitude (Cohen's $f^2 = 0.14$; see Selya et al., 2012). These results suggest that during the self-disclosure task, individuals with similar scores on Extraversion (similar dyads) exhibited stronger synchronization, in this case, turn-taking because of the negative value of synchronization (see Figure 3). In contrast, dyads composed of an introverted and an extroverted individual showed more simultaneous interpersonal synchronization. Overall our similarity hypotheses were only supported during the self-disclosing task for Extraversion, as we did not find significant effects for Agreeableness.

*3 The model structure was the following: [Synchronization ~ (Agreeableness A * Agreeableness B + Extraversion A * Extraversion B) * Type of Interaction + (1|Dyad)], where "A" and "B" correspond to each interacting partner. Consult Bates et al. (2015) to see more detail about the 'lmer' package and model terms.*

4 Observed power was calculated with the 'pwr' R package from conditional R2 (Champely et al., 2022); and Cohen's f-squared was calculated with the 'effectsize' package (Ben-Shachar, 2020). This refers to the full model and differs when evaluating each specific fixed effect.

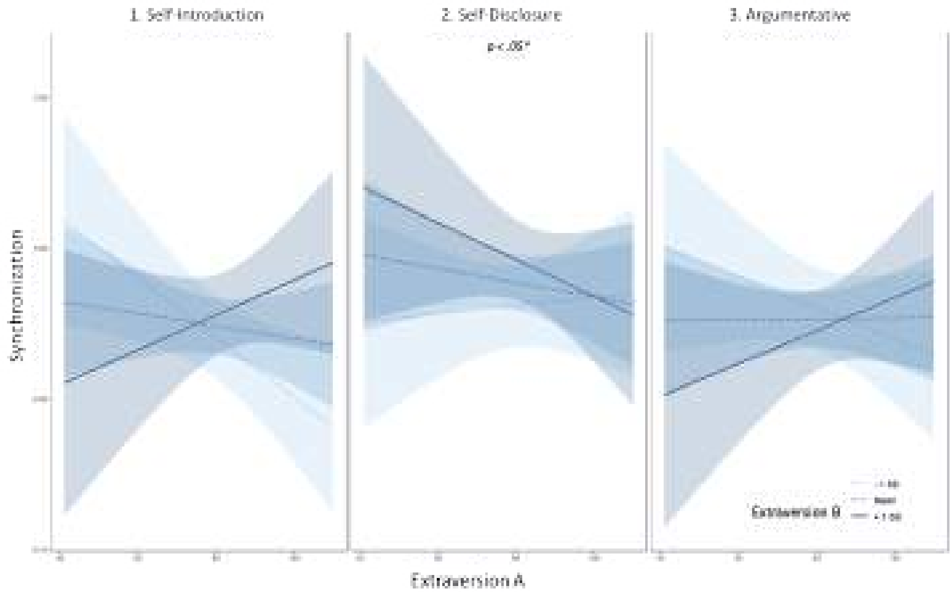
In addition, Synchronization strength was significantly inversely correlated with Determinism ($r = -.51$, $p < .05$) and Entropy ($r = -.52$, $p < .05$), which is explained by the quality of synchronization (negative/turn-taking, see Table S1).

Table 2. Descriptive statistics

Variable	Mean	SD	Min	Max	Median	CI (95%)
Interpersonal Synchronization (Grand Average WLCC)						
Synchronization Strength	-0.018	0.03	-0.08	0.04	-0.20	[-0.023 to -0.013]
Coupled Dynamics (CRQA)						
Determinism	0.93	0.03	0.79	0.97	0.93	[0.93 to 0.94]
Entropy	2.32	0.21	1.57	2.79	2.28	[2.28 to 2.36]
Laminarity	0.97	0.01	0.91	0.99	0.97	[0.96 to 0.97]
Mean Line	5.94	1.20	3.99	9.41	5.5	[5.72 to 6.17]
Personality Traits						
Agreeableness	86.62	11.05	44	111	87	[84.55 to 88.68]
Extraversion	78.05	15.57	40	110	80	[75.12 to 80.99]
Self-report Pre-Post Interaction Assessment						
Positive Affect (pre)	14.48	3.9	7	22	15	[13.75 to 15.21]
Positive Affect (post)	15.72	3.99	6	25	16	[14.98 to 16.47]
Negative Affect (pre)	8.32	3.33	5	20	7	[7.70 to 8.95]
Negative Affect (post)	6.40	2.41	5	21	6	[5.95 to 6.85]
Interpersonal Closeness	4.70	1.14	1	7	5	[4.48 to 4.91]
Enjoyment	3.84	0.69	1	5	4	[3.71 to 3.97]

Same gender dyads. N = 112 (56 dyads). CI, 95% confidence intervals.

Figure 3. Predicted values of Interpersonal Synchronization Strength depending on Extraversion scores



Note: The plot represents the fixed effects of Synchronization strength depending on the scores of Extraversion of both participants in the different types of conversation: Participant "A" on "X" axis, Extraversion of participant "B" is represented by three different lines (mean and +/- 1SD). During the Self-disclosure interaction, the effect of Extraversion of both conversation partners is statistically significant (p<.05) with the introduction as the baseline. When self-disclosing, synchronization increased for dyads with similar Extraversion scores (introverts and extroverts), exhibiting turn-taking behaviors (negative values of synchronization); synchronization decreased for dyads composed of a high and a low extraverted individual.

3.3. Dynamic Organization of Interpersonal Synchronization: CRQA of Body Motion

To examine the Dynamic Organization of Interpersonal Synchronization and personality effects, ML mixed-effects models were fitted using the very same structure mentioned in the previous model. Four models estimated the fixed effects of Agreeableness and Extraversion scores for each member of the dyad, and the type of interaction on Determinism, Entropy, Laminarity and Mean Line (see equations in Supplement to method S2).[5] The models included a random intercept at the dyadic level. All the continuous predictors were centered and rescaled to prevent convergence issues and we controlled for False Discovery Rates. We hypothesized stronger synchronization among individuals with similar scores on Agreeableness and Extraversion, and moderate synchronization among individuals with dissimilar scores on Agreeableness and Extraversion, and low synchronization among low agreeable individuals.

The observed global effect sizes at a significance level of 0.01 with a sample of 112 participants for each model are: Determinism (R^2= 0.39, ICC = 0.27; Cohen's f^2= 0.63, large); Entropy (R^2= 0.55, ICC = 0.27; Cohen's f^2 = 1.19, large); Laminarity (R^2= 0.58, ICC = 0.54; Cohen's f^2 = 1.38, large), and Mean Line (R^2= 0.54, ICC = 0.47; Cohen's f^2= 1.18, large). These values account for the percentage of variance explained by both fixed and random effects (based on conditional R-squared) of the full models. It is also relevant to mention the degree of Intraclass Cross-Correlation given by the dyadic structure in the models of Laminarity and Mean Line (54% and 47% respectively), suggesting a moderate between-dyad variation, indicating that the differences between dyads are a relevant factor to consider.

According to the results, Entropy was predicted to be higher as the Agreeableness scores increase (estimate = 0.11, p = 0.03, Table S2) (see Figure 4A). The local effect size for this effect is small (f^2= 0.08). The results suggest that if at least one dyad member exhibited low Agreeableness, the values of Entropy were expected to be lower, and in the case of high Agreeableness in at least one interacting partner, the values of Entropy increased. The specific effects for Agreeableness on the Determinism, Laminarity, and Mean Line models (in Supplementary Table S1) were not significant after correcting for False Discovery Rate.

The presence of at least one highly extraverted conversation partner in a dyad was linked to higher values of Mean Line during the argumentative conversation (estimate = 0.71, p = 0.02), especially during interactions with introverted people, indicating more stable synchronization in comparison to introverted or extraverted dyads (see Figure 4B). This local effect size is small (f^2 = .09). During the argumentation phase, there was just a marginal effect (non-significant after correcting for false discovery rates) on Entropy (estimate = 0.09, p = 0.07) and Mean Line (estimate = 0.46, p = 0.07) irrespective of personality scores. In sum, Agreeableness was linked to the dynamic organization of synchronization, particularly to the expected values of Entropy, being lower for low agreeable individuals and higher for agreeable dyads. Personality similarity in Extraversion did not significantly affect the dynamic organization, and we observed more synchronization (Mean Line) between dyads composed of an introvert and an extrovert

*5 The models followed the structure: [Determinism ~ (Agreeableness A * Agreeableness B + Extraversion A * Extraversion B) * Type of Interaction + (1|Dyad)], where "A" and "B" correspond to each interacting partner. Consult Bates et al. (2015) to see more detail about the 'lmer' package and model terms.*

individual during argumentative conversations. Correlations are presented in Table S1 and the full models are provided in Table S2.

3.4. Predicting Affective Experience, Interpersonal Closeness, and Perception of the Interaction

We expected that differences in dyadic synchronization of body motion would become reflected in how the conversation felt (affect valence), interpersonal closeness, and enjoyment of the conversation. Particularly, we expected that agreeable dyads and similar extravert dyads would report more positive affect and interpersonal closeness, and lower negative affect than dissimilar agreeable, extraverted dyads, and disagreeable dyads did. Linear models were performed, and for each response variable (post-conversation), a model was fit, thus Positive Affect, Negative Affect, Interpersonal Closeness, and "Enjoyment of the conversation". The predictor variables in the models were Interpersonal Synchronization Strength (from WLCC), as well as the CRQA variables of Determinism and Laminarity. We decided to include two CRQA variables in order to perform informative but also parsimonious models (see Table S3). These three variables were selected because of their low inter-correlation as they also provide information on different features of the cross-recurrence plot. Determinism gives information about diagonal structures, and Laminarity provides information about vertical lines. We decided to employ full interaction variables (15-minute conversations) instead of the three types of sessions to obtain simplified models. All the predictor variables were centered and rescaled, and we controlled for False Discovery Rates.

3.4.1. Affective Experience

Post-conversational positive affect (R^2= 0.31; f^2 = 0.45) was predicted by higher Extraversion (p = 0.01; model p < 0.001; f^2 = 0.10, Figure 5). Regarding negative affect (R^2= 0.49; f^2 = 0.97), if at least one interacting partner was low on Agreeableness negative affect was expected after the conversation (estimate = -0.83, p = 0.01; model p<0.001; f^2 = 0.12), and this effect was stronger among dyads who were both low on Agreeableness (p = 0.02; f^2= 0.09) compared to dyads composed by at least one (or both) agreeable individual(s) (see Figure 76). In correlational terms, positive affect before and after the conversation was significantly related to Extraversion (r = .65, p < .01 and r = .61, p < .05 respectively); negative affect before and after the conversation was linked to Laminarity (r = -.69, p < .01 and r = -.61, p < .05), Agreeableness (r = -.65, p < .01, r = -.67, p < .01), and Extraversion (r = -.62, p < .01, r = -.58, p < .01). All significant correlations are reported in Table S1.

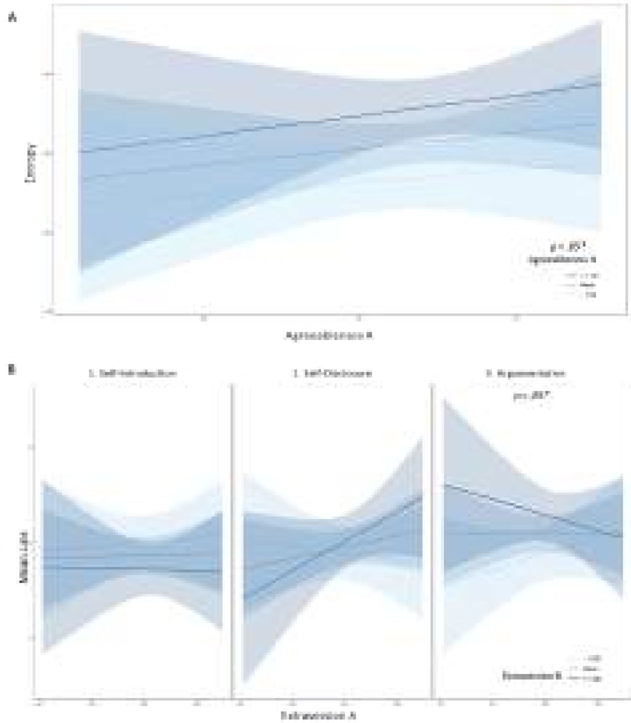
3.4.2. Interpersonal Closeness

The full model of interpersonal closeness was statistically significant (p <.001), nevertheless, after adjustment for False Discovery Rate, the specific fixed effects of the model became non-significant. Interpersonal closeness was positively correlated with the enjoyment of the interaction (r = .81, p < .01) and positive affect before (r = .51, p < .05) and after the conversation (r = .61, p < .05), see supplemental Table S1 and Figure 7.

3.4.3. Perception of the Interaction

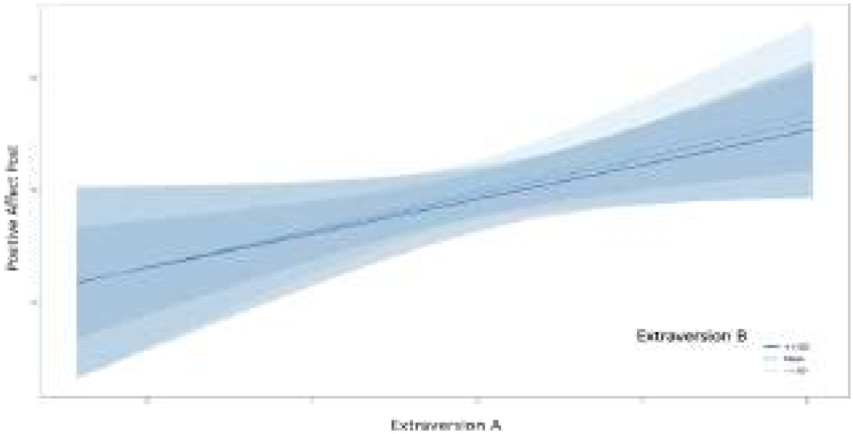
Conversations were judged to be more enjoyable (R^2= 0.38; f^2 = 0.60) when interactants exhibited higher Extraversion and fewer Laminar states in the synchronization dynamics (estimate = -0.44, p = 0.01; f^2= 0.11), while for dyads with dissimilar scores on Extraversion and for introverts, the presence of laminar states predicted more enjoyment (estimate = -0.33, p = 0.03; f^2 = 0.08; see Figure 7). The effect of Extraversion*Synchronization was marginal/non-significant (estimate = 0.18, p = 0.06) and this was similar for Agreeableness (p= 0.06) and Agreeableness*synchronization (p= 0.06). Finally, enjoyment correlated with positive and negative affect before (r = .55/-.58, both p < .05) and after the conversation (r = .64/-.65, both p < .01; see Table S1).

Figure 4. Predicted values of Dynamic Organization –Entropy and Mean Line – depending on Agreeableness and Extraversion scores respectively



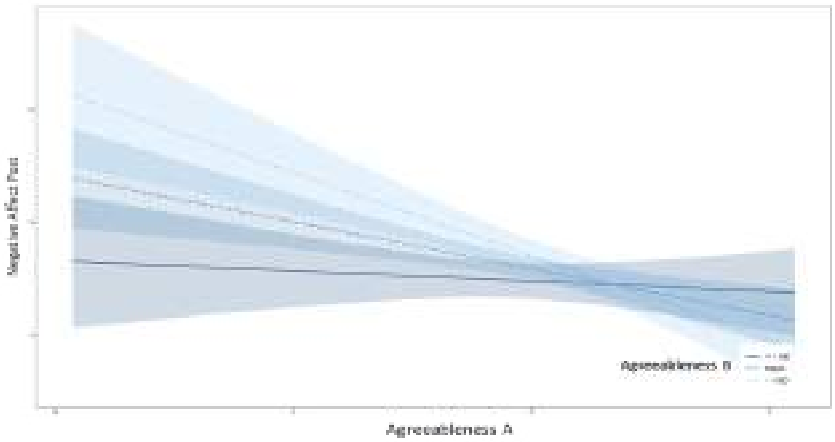
Note: The plots represent the fixed effects of Entropy (A) and Mean Line (B) depending on the scores of Agreeableness and Extraversion. Participant "A" on "X" axis, and participant "B" is represented by three lines of personality scores (mean and +/- 1SD). The plots show the predicted values over the full conversation (A, where low Agreeableness scores predict low Entropy p< 0.05); and different types of conversation (B), in which only the effects of Extraversion during the Argumentative conversation were significant (high scores of Extraversion predicted higher values of Mean Line, p< .05).

Figure 5. Predicted values of Positive Affect based on Extraversion scores of both conversation partners



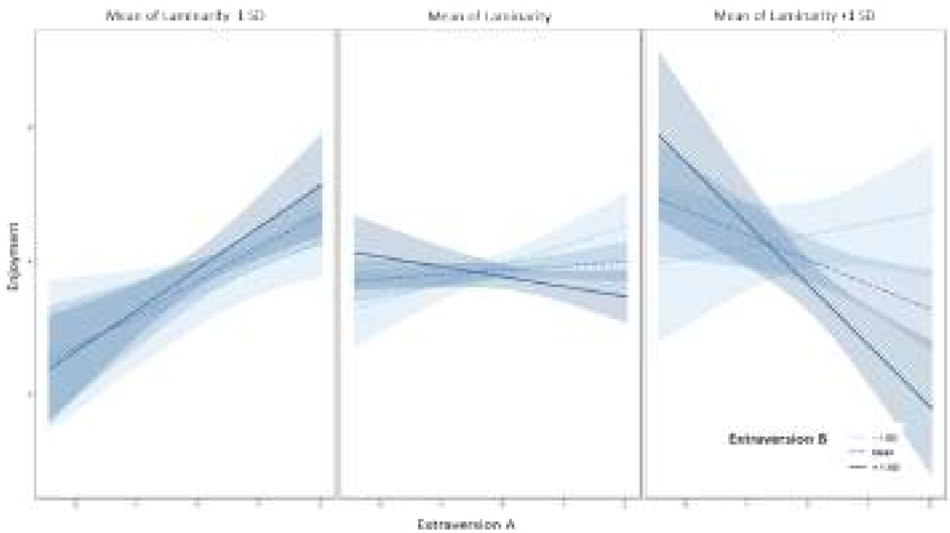
Note: The plot represents the fixed effects of positive affect post-conversation based on the Extraversion scores of both conversation partners (A and B). The predicted values of positive affect are predicted to be higher as the Extraversion scores of both interactants increase; and lower as the Extraversion scores of both interactants decrease.

Figure 6. Predicted values of Negative Affect based on Agreeableness scores of both conversation partners



Note: The plot represents the fixed effects of negative affect post-conversation based on the Agreeableness scores of both conversation partners (A and B). The predicted values of negative affect are predicted to be higher when interacting with individuals with lower Agreeableness scores, for individuals with higher scores in Agreeableness, negative affect tends to be low independent of their conversation partners.

Figure 7. Predicted values of Enjoyment based on Extraversion scores of both conversation partners and Laminarity



Note: The plot represents the fixed effects of enjoyment of the conversation based on the Extraversion scores of both conversation partners (A and B). The predicted values of enjoyment are predicted to be higher when there are fewer laminar states (-1SD) and the Extraversion scores of both conversation partners are high; while in the presence of more laminar states (+1SD), dyads composed by individuals with high and low scores on Extraversion tend to report more enjoyment.

4. Discussion

Our key observations were that differences in Agreeableness showed the strongest link to the dynamic organization of interpersonal synchronization, particularly to Entropy at the dyadic level, which indicates more complexity in the synchronization of interlocutors. Agreeableness was associated with low negative affect while disagreeable individuals reported more negative affect. When self-disclosing, personality similarity in terms of Extraversion also influenced the strength and quality of interpersonal synchronization, primarily through turn-taking patterns of movement. Introverts typically exhibited poor(er) dyadic synchronization and coupling (than extraverts did), except during self-disclosure conversations. More shared dyadic (laminar) states made people judge the conversation typically as more joyful, especially among Extravert participants. Finally, the conversational situations (self-disclosure/argumentative) impacted the strength of synchronization and dyadic coupling. The implications of the results for Agreeableness and Extraversion and their roles in interpersonal synchronization across conversational settings are now discussed in more detail below.

4.1. Agreeableness

We hypothesized (H1a) that agreeable dyads would exhibit higher synchronization strength and dyadic coupling. We observed stronger dyadic coupling only, in terms of Entropy, which we understood as indicative of the dynamic organization of interpersonal synchronization. Entropy captures the variety of patterns of coupling between the interacting systems and the visited trajectories in the reconstructed phase space (see Table 1 and McCamley, 2017). Entropy can be indicative of both high uncertainty and high dynamic complexity (in complex systems), versus more regular and predictable behavior in simple systems (Marwan et al., 2007; Nagaraj et al., 2017). Agreeable individuals were less predictable or more complex in their interaction patterns compared to less agreeable individuals across the full interaction. Agreeable people were thus more variable in the duration and occurrence of their bodily synchronization episodes, and more flexible and spontaneous in their movement patterns.

More agreeable people may show more active perception-action processes, exploration, and flexibility during interpersonal synchronization episodes, which are not necessarily conscious (e.g., Galbusera et al., 2019). Low-agreeable individuals, in turn, seem to exhibit more rigid, structured, fixated, and less complex movement patterns. This observed link between Agreeableness and complexity (Table S2) aligns with experimental evidence in which Agreeableness is associated with more dynamic movement patterns (e.g., phases of low/high activity/activation and relaxation, Koppensteiner, 2013). Entropy (i.e., unpredictability) can differ depending on the context and process which it expresses, such as mother-infant interactions in which more predictability and therefore low Entropy is desirable (Vanoncini et al., 2022); whether in other environments and systems dynamics, higher levels of Entropy can provide information about the complexity, flexibility of adaptation, learning, and functionality of behavior and processes (e.g., De Jonge-Hoekstra et al., 2020).

Higher levels of complexity and novelty (i.e., less predictability) in interpersonal interactions seem to be positively related to liking interaction partners (Ravreby et al., 2022). The increased systemic complexity could be also related to speech patterns and language (e.g., turn-taking dynamics and content, e.g., Tamis-LeMonda et al., 2017), considering language as an intrinsic multimodal process, with strong embodied cues playing a role (Alviar et al., 2023). But further research would be necessary in the field of personality. Note that the link between Agreeableness and Entropy had a small local effect size ($f^2 = 0.08$), which warrants cautious interpretations and external replication.

Additionally, agreeable dyads reported more positive affect, as expected, while disagreeable individuals were expected (H1b) and observed to show poor dyadic coupling and more negative post-conversational affect appraisals. Agreeable individuals are defined as cooperative, polite, kind, and friendly, and accordingly, our agreeable participants judged their interactions more positively irrespective of the dyadic constitution, in congruence with the literature (Berry & Sherman, 2000; Cuperman & Ickes, 2009). We observed that (dis)agreeable individuals influenced how their interaction partners would synchronize their body motion. Synchronization processes seem functional, but this function and/or goal can differ between individuals, personality traits, and situations. Disagreeable individuals seem to exhibit a higher desire to win when interacting with others (Urbig et al., 2021), for example, which could explain the more negative affect appraisals and less dyadic coupling (in terms of Entropy); while Agreeableness has been linked to thriving and maintaining positive interpersonal relationships (Jensen-Campbell et al., 2003), which can explain the flexibility in their behavior. Evidently, subtle patterns in interactants' behavior and dynamic organization are relevant to understand the complexity of dyadic interactions and the role of personality.

4.2. Extraversion

Dyads with similar Extraversion scores were expected (H2c) to synchronize more and appraise the interactions more positively (H2a-H2b) than dissimilar dyads would (H2c), for which weaker synchronization and more negative post-interaction outcomes were expected (more negative affect, low closeness, less enjoyment). We indeed observed that dyads with similar Extraversion scores exhibited stronger synchronization of turn-taking, especially when self-disclosing (H2a was supported); while introverted individuals generally exhibited weaker synchronization (no support for H2b). In this sense, both the type of conversation type and the interacting partner seem to be distinctive environmental influences (also see Breil et al., 2019, 2022). As previously noticed, the specific effects had a small effect size, which deserves cautious interpretations and external replication.

Dyads composed of individuals low and high in Extraversion exhibited more stable dyadic coupling (as expected) especially during the argumentative conversation (not in line with H2b), as expressed in terms of Mean Line (i.e., average duration of episodes of dyadic attunement in bodily movements, see definition in Table 1 and Figure 2 and McCamley, 2017). We observed stronger and more stable dyadic coupling in highly extraverted individuals, especially when interacting with introverts. Interestingly, the coupling of dissimilar dyads (more state Laminarity) resulted in more enjoyable conversations, suggesting that such moments of shared interpersonal states (predictability/consistency) are relevant to both introverts and extraverts.

Extraverted dyads, in contrast (thus without introverts), showed more flexible, less predictable, and less consistent conversations (fewer laminar states), but enjoyed these conversations more. As simulated and reported by Nowak et al. (2002, 2020), in interactions between dissimilar individuals, one of them is likely to adopt the behavior of the interacting partner subsequently (a process known as social influence), especially when the partner's behavior is strong and somehow corresponds to a "positive" state, which could also be linked to dominant behaviors (see Depue et al., 1999; Larsen et al., 2020). In other words, one of the interactants is likely to change their behavior to foster synchronization, thus s/he leaves their own equilibrium (baseline) to match the attractor state of the other individual (Nowak et al., 2020). And in the case of introvert/extravert interactions, it seemed to be functional to achieve positive outcomes like enjoyment even in competitive settings (Urbig et al., 2021). Furthermore, the increased coupling that resulted from the Mean Line model during the argumentative conversation, is congruent with the increased interpersonal synchronization reported by Tschacher et al. (2014, 2018) during competitive interactions, which could also be explained by the stronger attractor state of one of the individuals and the adaptation of the partner.

It is possible that introverted dyads did not leave their own attractor state, which future work may test. Future work may also focus more on the pace and content of the conversation, as dissimilar Extraversion dyads may revert to more scripted and topical interactions that are more balanced, as more introvert individuals may require more time (to think) before speaking which allows the extravert to fill the pauses with conversation. Extraverted dyads, in contrast, may converse more fast-paced, energetic, and excited, and interrupt each other in lively discussions, decreasing shared states, but giving rise to more interesting and pleasurable socializations overall.

4.3. Mutual Influence, Synchronization, and Dyadic Coupling: Summing up

Interpersonal synchronization is thought to promote mutual comprehension (Brennan & Hanna, 2009) and dyadic interactions in verbal tasks (Pickering & Garrod, 2004; Abney et al., 2014; Shockley et al, 2002), interaction quality (Reuzel et al., 2013) and an increased sense of "togetherness" (Ravreby et al., 2014). We outlined that some of the effects we observed could be driven by mutual influence (Thibaut & Kelley, 1959; Nowak et al., 2020) and understood by means of dyadic coupling (e.g., Konvalinka, et al., 2011; Abney et al., 2014; Schloesser et al., 2019). The higher-order functional unit (dyad) would exhibit different operational dynamics than the individual dynamics outside this dyadic setting (Vallacher et al., 2015); the other as the immediate environment.

As described in the introduction, an optimal degree of mutual influence is crucial for achieving dyadic synchronization, and we observed this optimum can differ between settings and dyads. Dissimilar agreeable and dissimilar extraverted dyads showed mutual influence, such dissimilarities played a role in inhibiting or promoting synchronization and systemic co-regulation (Vallacher et al., 2015). Furthermore, even when positive affect and enjoyment were associated with synchronization and dyadic coupling, this association was not observed for all personality traits, which could suggest that interpersonal synchronization has a different function for different personality traits, which may differ across phases of the lifespan (Siracusa et al., 2022) and situational synergies (Alviar et al., 2023). These functional mechanisms that connect personality to synchronization differences require further study.

Mutual influences can be understood from the perspective of enactive theories of cognition by means of a sensemaking process, by which living organisms do not engage passively in perceiving sensory stimuli, but individuals actively conduct their behavior based on (perceived) environmental significances (De Jaegher & Di Paolo, 2007; Corris, 2020). Particularly, agreeable individuals exhibited complex patterns of synchronization, with the emergence of flexible dynamics and higher exploration tendencies, which may be functional to their baseline features (Berry & Sherman, 2000). Disagreeable individuals may be less restricted in their interactions and individual goal approach strategies than social/affiliative people are (e.g., Urbig et al., 2021). The process of interpersonal synchronization seems to work as a functional mechanism promoting social or environmental outcomes, but these may not necessarily be pro-social outcomes. Interestingly, though perhaps not surprisingly, the type of environment, in the case of our study, the conversation partner and the type of conversation, influences this sensemaking process, such as during self-disclosing or argumentative conversations. We could argue that the degree of Agreeableness (Communion) and Extraversion (Agency) catalyzes the emergence of synchronization and dyadic coupling via sensemaking processes and by doing so helps individuals engage in continuous perception-action cycles (Satchell et al., 2021).

It has been argued that human thought is inherently dialogic as the window of consciousness in which humans can hold a thought or work things out is roughly seven seconds long, whereas conversations can extend over very long stretches of time (e.g., Graeber et al, 2021, p.94). Personality effects on interpersonal communication and synchronization may therefore be crucial to how humans learn to think about their worlds in support of conceptions of "personality" as a largely interpersonal phenomenon (Leary, 1957; Pincus et al., 2020). Embodied approaches have substantially described the body and face-to-face interactions as the substrate of the emergence of complex psychological, cognitive, and social phenomena (e.g., Thompson & Varela; Di Paolo & Thompson, 2014).

5. Limitations, strengths and future directions

Our study has some limitations, and probably the most relevant is our modest sample size. This made the estimates in our models conservative and replication efforts are required with larger samples (i.e. more nuanced associations may become significant in a larger sample), as some effect estimates became non-significant after correction for false discovery rates. We could add that these limitations were in part compensated by the time-series techniques developed for the exhaustive study of various aspects of dyadic synchronization, allowing us to identify relevant dyadic synchronization effects which aligned with theoretical expectations and previous studies. We also recognize the relevance of the type of interactions or situations, and in our study, the self-disclosure and argumentative conversations proved to be relevant. It would be desirable to test interactions with longer durations because five minutes per type of conversation might not be optimal to identify various interpersonal effects, and theorists should also mind the differences between first-contact interactions versus different types of close relationships (e.g., family, friends, acquaintances). In terms of generalizability, our sample of undergraduate students is specific, therefore it would be desirable to test such effects in a diverse population, as socialization behaviors are known to develop along the lifespan (Siracusa et al., 2022). Note that this sample of young adult students does allow us to focus more on personality differences in dyadic synchronization, because a more (age) diverse sample would also result in many additional socialization differences (Siracusa et al., 2022). Finally, our focus on two personality dimensions to study interpersonal dynamics is a (pragmatic) limitation given the interactive effects of different personality traits and the sheer range of possibilities. In this paper, we demonstrate a complexity approach to examine how personality differences connect to dyadic body synchronization and vary across types of conversation and we hope our methods and models stimulate future research on interpersonal personality processes.

6. Conclusion

Our study emphasizes the relevance of individual differences and contextual effects on bodily synchronization dynamics and dyadic coupling in a standardized conversation. We observed how differences in Agreeableness and Extraversion were connected to dynamic synchronization patterns in bodily movement and how the dynamics of the dyadic coupling of these interactions were recognizable across dyads. We were able to identify how interpersonal synchronization of body motion predicted how pleasant, close, and joyful interactions felt to participants. The interpersonal synchronization process in which each dyad was engaged and their personality traits were connected to the subjective experiences of each interactant. Finally, this study contributes to the understanding of personality from an embodied perspective, integrating the methods provided by the complex dynamic systems framework.

7. Data Availability Statement

Information and materials of this study can be accessed at the Open Science Framework: https://osf.io/xqgsa/

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9. Acknowledgments

We thank all participants of the study for their contribution. We acknowledge Mark Span (Ph.D.) for technical support on the experimental setup and Leslie Zwerwer (Ph.D. c) for her advice in data analysis. NA was supported by ANID, Chilean Government (Ph.D. Scholarship 72200122), and BJ by NWO-Veni 016.195.405.

Chapter 4

Personality expression in body motion dynamics: An enactive, embodied, and complex systems perspective

Published as:

Arellano-Véliz, N. A., Cox, R. F., Jeronimus, B. F., Castillo, R. D., & Kunnen, E. S. (2024). Personality expression in body motion dynamics: An enactive, embodied, and complex systems perspective. Journal of Research in Personality, 110, 104495. https://doi.org/10.1016/j.jrp.2024.104495

Abstract

We studied body motion dynamics and personality differences using complex systems methods. 105 adults (aged 18–33, 70% women) completed a 15-minute laboratory task covering three self-referencing topics (self-introduction, bodily perception/sensory life, socio-emotional life). Body motion dynamics were extracted from videos using a frame-by-frame differentiation method. Recurrence Quantification Analysis derived the measures of Determinism, Entropy, Laminarity, and Mean-Line. Multilevel models estimated personality (IPIP-NEO-120) and situational effects. Neuroticism predicted lower Determinism and fluctuating dynamics in bodily perception and socioemotional life; less complexity and stability during socioemotional topics, and increased negative affect. Extraversion predicted regular/deterministic dynamics during bodily perception. Conscientiousness predicted lower Determinism and increased variability. Agreeableness predicted lower post-task negative affect. Findings are discussed within embodied, enactive, complex systems, and personality frameworks.

Keywords: embodiment, dynamic systems, body movement, intra-personal dynamics, enaction

1. Introduction

Personality differences are expressed in body motion dynamics and we use semi-structured individual laboratory sessions to document their connection. We use enactive, embodied, and dynamic process perspectives as our theoretical framework to connect the cellular/organism level of analysis up to more abstract domains of behavior and mental processes (Varela et al., 1991/2017; Carruthers et al., 2005; Di Paolo et al., 2017; Hovhannisyan & Vervaeke, 2022), in keeping with our aim to connect body motion processes to personality structure. In the present study, young adults talk about three specific self-referencing topics to examine self-organizing dynamics captured from body motion (question 1), and subsequently, whether and which personality differences explain (part of the) variation in measures of dynamic self-organization of body motion (question 2). In addition, we included affective valence to assess how personality variation and the content of the three conversational topics influence how participants appraise their situation in a laboratory setting (e.g., Waugh & Kuppens, 2021). Our theoretical framework and methodological approach are summarized in Table 1 and outlined in more detail below, followed by our results and interpretation.

1.1. From the enactive approach to personality research

Enactive and embodied perspectives describe humans as self-organizing adaptive systems involved in a nonlinear and continuous exchange of energy and information with their environment (e.g., Di Paolo & Thompson, 2014; Fuchs 2017). The ***continuity thesis*** describes a continuum between basic life processes up to emergent psychological functionality such as emotion or personality structures that cannot be reduced to a brain or nervous system but that emerge from distributed processes throughout the whole organism and environments (i.e. are embodied; Varela et al., 2017; Thompson, 2010; Johnson, 2015; Fuchs, 2020). Enactive and embodied complex system perspectives assume that (a) human physical and mental organization and the material world share a fundamental set of (self-)organized features; and (b) the individual and environment continuously influence and constrain each other (Thompson, 2010; Varela et al., 2017; Galbusera et al., 2019).

This interconnectedness between individuals and their environment shapes how people behave, feel, and think, and is key to biological, developmental, personality, and social psychology (Tooby & Cosmides, 1992; Dawkins, 2016; Rauthmann, 2021). Each particular environment in which an individual is situated presents opportunities that influence the likelihood of the occurrence of behavior (Gibson, 1979; Rietveld & Kiverstein, 2014; Bruineberg et al., 2019), establishing nonlinear person-environment interactions (Davis et al., 2016; Schloesser et al., 2019). These person-environment interactions manifest through nonverbal features such as gazes, gestures, and body motion, which require coordination (both internal/external of the body) to achieve self-regulatory and communicative objectives (Blake & Shiffrar, 2007; Bloch et al., 2019; Chemero, 2013; Barrett, 2017).

Personality theory describes and explains how individuals explore, perceive, anticipate, and craft the world around them (e.g., Buss, 2019). Personality is conceptualized as relatively stable patterns of what someone feels, thinks, does, and desires over time and situations (Larsen et al., 2020; Wilt & Revelle, 2019). Some enactive and ecological theorists understand personality as stylistic individual differences in their perception of the world ("filters" or lens models), as well as in their selection, evocation, and creation of environments (e.g., Buss, 1991; Baron & Boudreau, 1987; Satchell et al., 2021). From a dynamic perspective, personality is a flexible system that adapts to situations and evolves over the lifespan, organized to cope with environmental demands (Vallacher et al., 2002; Nettle, 2006; Mischel and Shoda, 1995; Hovhannisyan & Vervaeke, 2022). Dynamic personality models adopt concepts from the complex dynamic systems theory to study the emergence, variability, and stability of personality (see Vallacher et al., 2002; Sosnowska et al., 2019).

1.2. Complex dynamical systems can bridge enaction and personality research paradigms

The convergence of complex systems and enaction principles presents an opportunity to connect with personality research paradigms (e.g., Fajkowska, 2015). This is achieved by recognizing that dynamics within various bodily modalities can serve as windows into psychological processes (Thompson & Varela, 2001; Michaels et al., 2021; Xu et al., 2020), as the body motion dynamics conserve or represent characteristic properties of the system as a whole (the person), just as the higher-order psychological processes do (e.g., Richardson & Chemero, 2014). Complex systems such as humans are composed of interwoven elements that result in spontaneous self-organization (Strogatz, 1994; Vallacher et al., 2013; Gallagher & Appenzeller, 1999) which results in the growth of increasingly complex organisms that develop novel behavior and strategies over time (Goodwin, 2001; Pross, 2016; Richardson & Chemero, 2014; Den Hartigh et al., 2017).

One class of dynamic personality models considers each adult as having a characteristic personality (***baseline***) in which each factor is conceptualized as an attractor in the psychological landscape (or network), while each individual shows fluctuating states (***variability***) in response to situational factors (Cramer et al., 2012; Sosnowska et al., 2019). An attractor represents a stable and dominant state, or dominant network of connections to which an unperturbed system naturally converges over time and returns after disruption (Vallacher, 2009; Kunnen & van Geert, 2012; Nowak et al., 2020). Within this view, the Neuroticism trait, for instance, can be seen as a macro-level attractor basin, which calibrates one's internal dynamics such that less environmental input is necessary to move toward specific micro (real-time) emotional states of anxiety or sadness (Jeronimus, 2019). Accordingly, self-organization is seen as the process that sustains stability but also underlies shifts in system dynamics when individual or environmental constraints push the system into a different attractor state (transitions, see Pross, 2016; Vallacher et al., 2013; Varela et al., 2017), and when mechanisms anchor the new attractor state, the changes may become more permanent (e.g., personality change, see Bleidorn et al., 2022; Jeronimus et al., 2014). Attractor strength reflects the swiftness with which an individual or any dynamic system returns to the baseline attractor and indicates organization (Sosnowska et al., 2020). The pull of a higher-order mental system coordinates the interactions between (lower-level) system elements (Nowak et al., 2020). When external influences temporarily push the system out of an attractor state the intrinsic dynamics of the system aim to return to (an) equilibrium over time (Vallacher, 2009). Individual differences in personality trait stability are described within such models as an individual's capacity to adapt to changing environments.

As an example, conscientious individuals (vs. low conscientious peers), are defined as more consistent over time, which can be described as a stronger attractor pull (Fetterman et al., 2010). In contrast, people high in Neuroticism (low emotional stability) show a heightened reactivity to stress and more diverse behaviors across situations (e.g., Xin et al., 2017), which can be described as a weaker attractor pull. These patterns illustrate the interplay of self-organizing processes across neural, cognitive, musculoskeletal, and social subsystems that might underlie personality factors (Buss, 2019).

1.3. Personality traits attribution from embodied cues

A more practical framework to connect enactive, embodied, and dynamic perspectives to personality research is the Brunswik lens model, which illustrates how people perceive others through a set of imperfect "cues" or objective distal indicators, such as body motion, or vocalic and linguistic signals, which in turn influence affect or thoughts (Brunswik, 1952; Bernieri et al., 1996; Burgoon et al., 2022). This lens model aligns with the notion that even brief glimpses of body motion can provide rich information about personality traits and has been used to describe the accuracy of personality judgments at zero acquaintance (Nestler & Back, 2013). Indeed, minimal body motion information such as major joint movement of animated stick figures (or point-light displays) without identifiable physical features (such as faces) suffices for observers to reliably ascribe differences in personality traits, dominance, trustworthiness, and competence (Koppensteiner, 2011, 2013, and colleagues 2016). Extraversion was associated with overall high, conspicuous, and variable motor activity; Neuroticism with high swaying and uncontrolled movements, contrary to emotional stability. Agreeableness was associated with stable and less expansive movements; and Openness with complex and variable movements (Koppensteiner, 2011, 2013).

Similarly, glimpses or thin-slices of target behavior of milliseconds or seconds suffice for humans to reliably attribute affective states, personality traits, and other relevant information (e.g., Ambady & Rosenthal, 1992; Ambady et al., 2000; Jiang et al., 2023). The higher interrater reliability for Agreeableness, Extraversion, and Conscientiousness suggests greater observer accessibility, whereas differences in Neuroticism and Openness were less accessible from behavioral snippets (e.g., Albright et al., 1988; Jiang et al., 2023). A meta-analytic study indicated that 30 seconds of exposure time sufficed to reach optimal personality judgment accuracy (Ambady & Rosenthal, 1992). Evidence suggests that negative affect, Extraversion, Conscientiousness, and intelligence are judged most accurately after five seconds, but it requires ~20 seconds of exposure time for positive affect, Neuroticism, and Openness to reach similar accuracy; and up to 60 seconds for Agreeableness to achieve the optimal ratio between stimulus exposure and accuracy (Carney et al., 2007; but underpowered). New studies emphasize that human accuracy in personality observation is situation-dependent and visual information is enriched with contextual understanding (Jiang et al., 2023).

1.4. Extending the framework: towards a novel empirical paradigm

Building on the dynamic personality models and personality judgment framework, we suggest that a rich empirical paradigm for examining personality is by observing people's embodied dynamic 'personality expression' from their attunement to the immediate environment (e.g. Arellano-Véliz et al., 2024a). This paradigm takes the immediate environment as a source of constraints on an individual's behavior. Such constraints come from various sources, for instance, those involved in one's posture and orientation in the room or in coordinating with another person (perception-action constraints), or those given by social conventions or a conversation topic (social constraints). Situational constraints play a relevant role in promoting behavioral attunement, as they foster the emergence of critical states, where system components are more likely to give rise to "emergent" system properties (Kelso & Schöner, 1988; Plenz et al., 2021), such as an emotion state (e.g., Barret, 2017), which is the core of self-organized criticality (cf. Bak & Wiesenfeld, 1987).

More concretely, we argue that the dynamical patterns in body motion, which can be extracted from brief episodes of attunement to the immediate environment, are a pure form of personality expression and are also associated with personality differences (e.g., Jiang et al., 2023). As an example, highly extroverted individuals may show movement patterns that embody their sociability and more kinetic activity, which expresses their dynamic approach and responsiveness to their surroundings (Luck et al., 2010). The immediate environment in such cases entails constraint given, for instance, by keeping an upright posture while standing and by a topic of a conversation, as already mentioned above. Both sets of constraints, and many more involved in any given situation, will continuously influence the self-organizing system as a whole and will be reflected in both personality processes (e.g., appraisal and meaning) and body motion dynamics (e.g., Paxton & Dale, 2017). In essence, from a complex dynamical systems perspective, body motion dynamics and personality processes both provide information about the system as a whole. This fundamental notion related to interdependence within complex dynamic systems is nicely captured in Takens's theorem, which will be explained below. By implication, they also provide information about each other, as they mutually and critically influence one another. The way they do, we argue, is expressed in how they unfold within a specific immediate environment.

As a corollary, this complementary perspective suggests that personality is not merely an abstract concept but an embodied and enacted process, which is expressed by body motion patterns while attuning to the immediate environment (e.g., mediated by affective and cognitive processes). This aligns with the process approach to personality (e.g., Baumert et al., 2017; Denissen et al., 2008) and the idea of behavioral signatures underlying personality systems (Mischel and Shoda, 1995; Brunswik, 1952). In this paper, we will extend these frameworks and examine body motion as a window on the emergent self-organizing patterns underlying personality expression to discern personality differences at the level of the person-environment system (cf. Vallacher et al., 2013; Nowak et al., 2020).

1.5. Current study

We investigated how personality differences are expressed in body motion patterns when a person speaks individually about three different self-referencing topics, in a semi-structured task.[1] Body motion dynamics were analyzed using Recurrence Quantification Analysis (RQA). In addition, we measured affect valence pre and post-task to capture the process or task appraisal to better understand personality effects in the laboratory setting. While the body motion dynamics serve as a tangible manifestation of how individuals engage with and respond to the situational constraints presented by the task, the affective valence measures the subjective appraisal of the embodied experience (e.g., Merleau-Ponty, 1945).

1.5.1. Introduction to Recurrence Quantification Analysis (RQA)

This study uses the Recurrence Quantification Analysis (RQA) technique, which is a nonlinear time series analysis employed to analyze temporal correlations and repetitive patterns within time series. In contrast to alternative approaches, RQA produces robust results with few assumptions such as normal distribution of the data, and providing information about the dynamic organization of a system (Marwan et al., 2007; Danvers et al., 2020; Shockley et al., 2022).

1 We refer to "task" or "session" indistinctly as the full 15-minute experiment. We refer to "topic" or "self-referencing topic" when we talk about the three different parts of the session (high-level constraints, see method section for details).

Recurrence is a fundamental characteristic of complex dynamical systems, defined as a system's tendency to return to the proximity of its initial point. By quantifying the patterns of such recurrences (Marwan et al., 2007), RQA captures the temporal organization of complex dynamical systems regarding the extent of deterministic episodes, stability, complexity, and flexibility, among others. Its utility extends to pattern detection and changes in time series that are difficult to analyze with traditional methods, and it has been employed in diverse settings such as laboratory studies and ambulatory assessments (Dale et al., 2011; Lichtwarck-Aschoff et al., 2012; Lira-Palma et al, 2018). RQA reconstructs the phase space of a system based on Takens' embedding theorem (1980), which shows that one can approximate the phase space of a dynamical system by creating surrogate dimensions using the delay-embedding technique. That is, the system's multidimensional phase space can be reconstructed from a single of its constituent time series variables by simply making copies of them with some time delay and treating them as the additional variables of the system. Therefore, RQA simplifies the complex dynamics of a system from a multidimensional phase space into a more comprehensive reconstructed two-dimensional representation, which is visualized in recurrence plots (see Figure 1; Zbilut & Webber, 2006; Marwan et al., 2007; Morales-Bader et al., 2023).

Recurrence plots visualize the recurrences in the behavior of a system (such as in Figure 1), that is, repeating states of the system, which are depicted by patterns of black and white dots (or in a matrix of ones and zeros) (Marwan et al., 2007; Konvalinka et al., 2011; Webber & Zbilut, 2005). The recurrence plot represents the system's dynamics with diagonal and vertical structures as indicative of non-random patterns or "deterministic processes" among stochastic elements (see Riley et al., 1999; Marwan & Webber, 2015). Diagonal lines in the recurrence matrix represent sequences of states that repeat over certain trajectories or different times, providing information about the system's regularities, attractor states, and overall dynamics. However, when diagonal lines appear alongside single isolated points, they might signify chaotic processes, indicating instability within the system (Marwan et al., 2007). Vertical structures in the matrix signify instances when the system remains in the same state for a period of time or changes only gradually (Spiegel et al., 2016; Cox et al., 2016; Tommasini et al., 2022). Vertical lines are also an indication of Laminarity (Marwan et al., 2007). By quantifying these structures, the recurrence plots can provide insights into the dynamics of a system, in terms of patterns, trends, trajectories, and changes. Note that there is no direct link between a specific observed behavior (e.g., someone moving an arm) and a specific structure in the recurrence plot. Instead, the recurrence plot captures the underlying dynamic organization of the system producing the behavior.

We extracted the following RQA metrics to operationalize the dynamic self-organization: Determinism, Entropy, Laminarity, and Mean Line (see Table 1). Determinism quantifies the percentage of recurrent points that form diagonal line structures, representing a systematic and patterned organization (Marwan et al., 2007). Determinism reveals the deterministic patterns or recurring episodes of the system in phase space (Konvalinka et al., 2011). High Determinism signifies more organized and predictable dynamics (Figure 1A), as the system consistently revisits sequences of the same states in a well-ordered and patterned manner (Marwan et al., 2007).

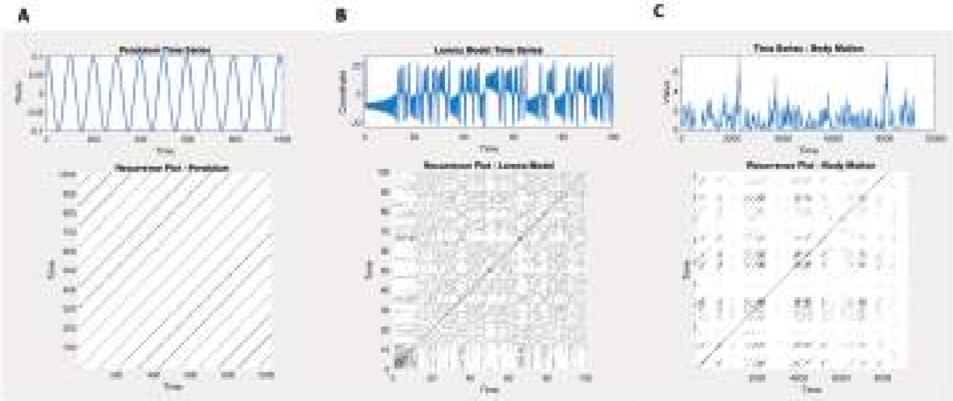
Information Entropy is a measure of the system's disorder or the level of uncertainty present in a signal, and in RQA it can be used to characterize the complexity of the system (Webber & Zbilut, 2005). Entropy is estimated by applying the Shannon (1948) formula to the frequency distribution of the lengths of the diagonal lines that are present in the recurrence plot (Marwan, 2007). By doing this, we are essentially measuring the information or uncertainty/certainty associated with these patterns. A highly repetitive distribution of the lines will indicate lower Entropy, and it can be interpreted as low complexity, as is the case of a pendulum oscillator (see Figure 1A). A system with relatively high levels of Entropy can also have regular behavior, as in the case of complexity in real-life adaptive systems (see Figure 1C), which is not a random occurrence. In other words, the complexity observed in adaptive systems reflects a balance between order and randomness, neither excessively chaotic nor overly repetitive (López-Ruiz et al., 1995; Clark & Jacques, 2012).

Laminarity is the percentage of recurrent points within the phase space that form vertical lines, representing cohesive laminar patterns (Marwan et al., 2002). These laminar patterns or laminar states signify segments in the dynamics where the system maintains a relatively stable state with sustained recurrence. Elevated Laminarity values imply that the system spends an extended duration in specific (attractor) states before undergoing a transition to a different state. Conversely, lower Laminarity values suggest a more erratic behavior, where recurrent points are scattered and lack organization into sustained, connected structures (Marwan et al., 2002; Webber & Zbilut, 2005). In this way, Laminarity also provides information about the intermittency of the system.

Mean Line length can be interpreted as a measure of overall stability in the system's dynamics, as it measures the average length of all diagonal structures in the recurrence plot (Marwan, 2007). It provides a global overview of the recurrent patterns and their average duration in the phase space (see Figure 1, and Table 1 provides definitions and interpretations). More details about the RQA technique are given in the method section.

In the context of this study, differences in these RQA measures between the conditions or between personality traits suggest differences in this dynamic organization. This can be visualized with the following example recurrence plots, which display markedly different systems (Figure 1): A) a simple pendulum, B) the Lorenz system, and C) a real body motion time series. The pendulum system exhibits highly deterministic and regular behavior characterized by consistent oscillations (Marwan et al., 2007). Its motion follows a repetitive pattern with regular oscillations, continually transitioning between the same states without extended periods of stillness. As a result, the recurrence plot does not show vertical lines, indicating the absence of laminar states. The Lorenz attractor represents a highly complex system that tends to exhibit chaotic behavior and sensitivity to initial conditions, yet it exhibits attractor states, and patterns and follows specific equations (Lorenz, 1963). Third, a recurrence plot based on real data shows distinct patterned structures that combine regularity with varying levels of stochasticity, deterministic patterns, and noise.

Figure 1. Examples of different systems' Recurrence Plots



Note: Examples of different systems' Recurrence Plots Note: The figures illustrate recurrence plots of three distinct systems. In Panel A, we observe the simulated recurrence plot of a simple pendulum oscillation, representing a highly deterministic and patterned system (DET = 0.99, ENT = 0.61, LAM = 0, ML = 37.84). Panel B displays the recurrence plot of the Lorenz system (DET = 0.64, ENT = 3.71, LAM = 0.88, ML = 7.37), representing a complex system that tends to exhibit chaotic behavior, sensitivity to initial conditions (small changes in the initial conditions can lead to different outcomes over time), and the presence of attractors which are complex geometric structures that represent the long-term behavior of the system (Lorenz, 1963). In Panel C, we present the real RQA plot derived from a real body time series, which reflects real behavior, which is patterned, presents laminar states, and also exhibits stochastic behavior (DET = 0.90, ENT = 2.84, LAM = 0.95, ML = 10.11). Further details about the dynamic measures can be found in Table 1. The recurrence plot's visual characteristics provide information about the systems' dynamics. Influenced by the phase space trajectory, the plots exhibit small-scale structures like singular dots, diagonal lines, and vertical/horizontal lines (or a combination forming extended clusters) (Zbilut and Webber, 2006; Marwan et al., 2002). These plots were generated using the RQA toolbox in Matlab (Ouyang, 2023). The values of each RQA variable are just referential, as they may vary for different systems depending on their specific properties and parameter settings (e.g., embedding dimension and delay).

Table 1. Variables Definition and Interpretation (*)

Dynamic Self-Organization: Intrapersonal dynamics of body movement based on Motion Energy Analysis		
Technique: Recurrence Quantification Analysis (RQA), a nonlinear time-series analysis, is used in this study for measuring the temporal structure and self-organization of body motion.		
Variable	**Definition**	**Interpretation**
Determinism (DET)	Proportion of recurrences ≥ 4 along diagonal lines in the recurrence plot, where line length or periods of recurrences vary.[1-3]	Estimates deterministic patterns of the time series in terms of signal regularity.[2,4] Higher DET values (closer to 1, on a scale of 0-1) tend to indicate more consistent, recurrent patterns (visited repeatedly) and highly assembled signals in the system dynamics.[1,2]
Entropy (ENT)	Shannon Entropy of the distribution of diagonal line lengths in the recurrence plot captures the range of patterns that couple the time series and type of paths that the systems visit in the reconstructed state space.[2,3]	Low(er) ENT values suggest a greater likelihood of repeating and regular paths. Higher ENT values suggest greater heterogeneity in the duration of recurrent paths or trajectories.[5] Higher values can indicate both higher complexity/flexibility and irregularity in the system trajectories.[2,6] Complexity can be understood as an interaction between Entropy (information) and (dis) equilibrium.[7]
Laminarity (LAM)	The proportion of recurrent points forming vertical lines in the recurrence plot quantifies the occurrence of laminar states in the system, which indicates intermittency(**) It is analogous to DET but Laminarity measures the proportion of recurrences in the vertical lines instead of diagonal lines.[8,9]	Laminar states describe periods of relatively stable and regular system behavior (attractor) while low(er) LAM values indicate more variable system dynamics.[4,5,10] Laminar structures are episodes in which the system is "captured" in a particular state known as an attractor state.[8,9]
Mean of diagonal line length (ML)	The Mean diagonal line length (ML) of all diagonal lines in the recurrence plot describes the overall plot structure. It estimates the average time by which two segments of a trajectory are close to each other.[3,6]	Estimates system stability as short ML indicates irregular dynamics and longer ML indicates stable and regular dynamics.[3]

Note: (*) Table adapted from Arellano-Véliz et al. (2024a). (**) Intermittency refers to an irregular alternation of phases of apparently periodic (organized) and chaotic (disorganized) dynamics. 1 Curtin et al. (2017). 2 McCamley et al. (2017). 3 Marwan et al. (2007). 4 Konvalinka et al. (2011). 5 Tommasini et al. (2022). 6 Wallot & Leonardi (2018). 7 López-Ruiz et al. (1995). 8 Marwan et al. (2002). 9 Webber & Zbilut (2005). 10 Dimitriev et al. (2020). For equations of each RQA measure, see Tommasini et al. (2022).

We hypothesized that (H1) self-referencing topics provide a "high-level situational constraint" that predicts (part of) the dynamic self-organization in body motion operationalized by RQA measures. We anticipated that personality differences have an interactive effect on how these conversational topics influence body motion dynamics (H1b). Previous reports on a dyadic task with similar characteristics as high-level constraints (introduction/self-disclosure/argumentative), showed associations with personality traits, and synchronization of body motion expressed by the variables of Entropy, Determinism, Laminarity, and Mean Line (Arellano-Véliz et al., 2024a). Earlier studies found similar effects on three different social tasks (competition/cooperation/fun) also identifying effects on interpersonal synchronization of body motion (Tschacher et al., 2018). Similarly, friendly versus argumentative discourses showed significant effects of high-level constraints on dyadic movement dynamics (Paxton & Dale, 2017). We expected that if these effects were observable in interpersonal settings, they extend to what individuals do when they are alone, as in ways we seem to act most alike (Larsen et al., 2020). We argued that the shared situational constraints and temporal characteristics provide a basis for expecting meaningful differences (e.g., Klimstra et al., 2018). We further based our hypotheses on the general literature on personality and considered the available previous studies using RQA in the context of personality traits but in other settings (e.g., Danvers et al., 2020; Jiang et al., 2023). However, to our knowledge, no studies employing identical measurements in a task akin to the current one have been conducted.

We reasoned that sensorimotor systems capable of flexibly attuning to different environments and situations would exhibit systemic stability and complex behavior (e.g., De Jonge-Hoekstra et al., 2020). Essentially, this skillful attunement will enable individuals to self-organize themselves and to be responsive to environmental affordances (Bruineberg et al., 2019). In this sense, complex behavior arises from the interplay of Entropy and equilibrium, fostering a functional, flexible, and adaptive state (López-Ruiz et al., 1995). System stability (self-organization) is expected to be reflected by complexity (positive effects on Entropy), regularity (positive effects on Laminarity), stability (positive effects on Mean Line), and deterministic patterns (positive effects on Determinism; Manor et al., 2010). These ideas delineated the basis for personality trait-specific hypotheses in alignment with the general expectation (H2) that personality traits would predict (a part of) individual variation in the dynamic self-organization of body motion. Our expectations were delineated as follows (see Table 2):

Extraversion as the most expressible personality trait (e.g., Albright et al., 1988; Kenny et al., 1992; Jiang et al., 2023) captures differences in flexibility, novelty seeking (DeYoung, 2013), and resilience (Oshio et al., 2018). Higher scores on Extraversion were expected to be associated with adaptive self-organizing behaviors as indicated by higher Entropy (interpreted as complexity/flexibility), Determinism (patterned behavior), Laminarity (laminar phases where the system visits and fixates in certain states), and

Mean Line (higher system stability) (H2a).

Neuroticism captures unstable patterns of body motion (Koppensteiner, 2013), and it is characterized in the literature by anxiety and volatility in emotion dynamics (Mader et al., 2023). Neuroticism was expected to be associated with less adaptive dynamic self-organization than other traits, thus lower system Entropy (interpreted as lower complexity), Laminarity (less laminar phases or more volatility), Determinism (less patterned behavior), and Mean Line (less system stability) (H2b).

Agreeableness is typically characterized by cooperativeness, kindness (McCrae & Costa, 2008), and motor stability (Koppensteiner, 2013). In previous studies, Agreeableness has been linked to higher Entropy and coupling in interpersonal settings (Arellano-Véliz et al., 2024a). High Agreeableness was expected to predict adaptive dynamic self-organization evidenced by higher Determinism (patterned dynamics), Entropy (interpreted as complex and flexible patterns), Laminarity (presence of laminar phases), and Mean Line (system stability) (H2c).

Conscientiousness captures responsibility, orderliness, and prioritization of non-immediate goals (DeYoung, 2015). We anticipated that these characteristics would be reflected in organized and controlled movement patterns, reflected as stronger system self-organization given by higher Determinism (highly patterned behavior), Entropy (interpreted as complexity), Laminarity (presence of laminar phases/fixated states), and Mean Line (system stability) (H2d).

Openness to experience is characterized by intellectual curiosity and creativity (McCrae & Costa, 2008). High Openness to experience has been associated in the literature with body motion direction and variability (e.g., Koppensteiner, 2013) and dyadic attunement (synchronization, see Tschacher et al., 2018). We predicted lower Determinism (less deterministic patterns), which may be linked to behaviors of exploration and novelty (Gocłowska et al., 2019), higher Entropy (interpreted as complex and flexible patterns of movement), lower Laminarity (more flexible and smooth laminar states), and higher Mean Line (system stability) (H2e).

Finally, we generally expected to find differences in the predictive effect of personality traits on affect valence, especially post-task (H3). This measurement was mainly exploratory. We reasoned that the high-level situational constraints of the task would be reflected in the participants' appraisal. We expected that personality traits that exhibited adaptive patterns of self-organization (i.e., stability, patterned behavior, laminar phases, and complexity) would predict positive post-task appraisals (e.g., Koch, 2014; Jenkins et al., 2021).

Table 2. Summary of hypotheses by personality traits and RQA variables

Variable	DET	ENT	LAM	ML	Explanation
Extraversion	Positive effects	Positive effects	Positive effects	Positive effects	Extraversion as the most expressible personality factor (e.g., Albright et al., 1988; Kenny et al., 1992; Jiang et al., 2023) captures differences in flexibility, novelty seeking (DeYoung, 2013), and resilience (Oshio et al., 2018). High scorers were expected to show adaptive self-organizing behavior reflected in regular patterns, complexity, laminar phases, and stability (H2a).
Neuroticism	Negative effects	Negative effects	Nega-tive effects	Nega-tive effects	Neuroticism captures more unstable patterns of body motion (Koppensteiner, 2013) and emotion dynamics (Mader et al., 2023). Neuroticism was expected to be associated with less adaptive dynamic self-organization than other traits reflected in less patterned, complex, and stable dynamics (H2b).
Agreeable-ness	Positive effects	Positive effects	Positive effects	Positive effects	High Agreeableness was expected to predict adaptive dynamic self-organization evidenced by more complex/flexible, patterned, and stable dynamics of movement (e.g., Arellano-Véliz et al., 2024a) (H2c).
Conscien-tiousness	Positive effects	Positive effects	Positive effects	Positive effects	Conscientiousness captures orderliness and prioritizing non-immediate goals (DeYoung, 2015), anticipated to be reflected in organized/controlled, complex, patterned, and stable movement dynamics (H2d).
Openness to Experience	Negative effects	Positive effects	Nega-tive effects	Positive effects	High Openness to experience is associated with body motion direction, variability (e.g., Koppensteiner, 2013), and dyadic attunement (synchronization, see Tschacher et al., 2018). We predicted more complex/ flexible, stable, and explorative patterns of movement (Gocłowska et al., 2019) (H2e).

Note: More information about each RQA variable can be consulted in Table 1. All general predictions were pre-registered.

2. Method

2.1. Sample

We invited students from the University of Groningen to participate who were rewarded with European Credit Transfer and Accumulation System (ECTS) credits. Initially, 115 students attended the laboratory session, but our final sample size was 105 participants (age range 18-33, mean age = 20.48, SD = 2.6), as ten of them lacked complete or usable data. Approximately 300 students were screened (same screened sample as in Arellano-Véliz, 2024a). Our sample (70% women, 30% men, 0% other) came from diverse backgrounds (50% Dutch, 26%, German, and 24% other). This study was approved by the Ethical Committee for research with human participants of the Faculty of Behavioural and Social Sciences, University of Groningen, Netherlands.

2.2. Self-report

2.2.1. Personality traits

Personality traits were measured using the publicly available IPIP-NEO-120 (Johnson, 2014) via the online Qualtrics platform before the laboratory study was conducted. The IPIP-NEO-120 is a self-report questionnaire with 120 items designed to assess the five major personality traits: Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness, along with their 30 facet traits (Johnson, 2014). The IPIP-NEO-120 showed good psychometric properties comparable to those of the NEO-PI-R scales (Costa & McCrae, 2008), which indicates that the IPIP-NEO-120 is a reliable and valid measure (see items and facets on https://ipip.ori.org/30FacetNEO-PI-RItems.htm). In a sample of 501 individuals, the IPIP-NEO-120 showed high correlations with the NEO-PI-R scales (Neuroticism 0.87; Extraversion 0.85; Openness to Experience 0.84; Agreeableness 0.76; and Conscientiousness 0.80, all p<.01). The IPIP-NEO-120 also demonstrated good internal consistency, with Cronbach's alpha coefficients of 0.88, 0.84, 0.85, 0.81, and 0.84 for each trait, respectively.

2.2.2. Affect Valence (process assessment)

Positive and negative affect states were measured with the 10-item self-report I-PANAS-SF instrument (Thompson, 2007) before and after our task. The I-PANAS-SF examines the extent to which five positive affect adjectives (determined, attentive, alert, inspired, and active) and five negative affect adjectives (afraid, nervous, upset, ashamed, and hostile) apply to oneself at the present moment (we adjusted the instruction to measure affect state), reported on a 5-point Likert scale from 1 (very slightly) to 5 (extremely). Composite scores for positive affect (PA) and negative affect (NA) were calculated by summing the item scores. The psychometric properties of the I-PANAS-SF were comparable to the original 20-item PANAS, with high correlations for both PA ($r = 0.92$) and NA ($r = 0.95$, both $p < .01$; Thompson, 2007). The I-PANAS-SF demonstrated adequate test-retest reliability ($N = 143$, $r = 0.84$ for both PA and NA, $p < .01$) and good internal consistency, with Cronbach's alpha coefficients ranging from 0.72 to 0.78 (Thompson, 2007), which are similar to those of the original 20-item PANAS version (Watson et al., 1988).

2.3. Procedure

When the participants arrived at the laboratory, they were asked to read the informed consent and to wear a heart rate belt (this data is not part of this paper). Participants were instructed to speak in front of a camera about themselves for 15 minutes on three broad and increasingly personal topics. They were standing on a posture tracking board (data not reported in this paper), which also served as a marker for the exact position to be recorded. The experimenter (female) stayed in the same room behind a screen to not disturb the participants. The participants were asked to talk as openly and freely as they wanted about themselves as if they were speaking to someone they never met before. The topics were defined as follows: 1) Introducing oneself; 2) bodily perception/ sensory life; 3) socio-emotional life. Some guiding questions or subthemes were given together with the instructions in case they needed some directions, for example, for topic *1: "What is your name and age?", "how does a normal day look like for you?"; topic 2: "How would you describe the way your body feels when you move? (e.g., you feel it graceful, heavy, light, energized, tired)"; "Could you describe how your body feels when you are sad or upset?"; topic 3: "How do you describe your childhood and family life?"; "How do you describe your social relationships at the moment? How do you feel about them?"; "How do you experience the times in solitude?")*[1]. These guiding questions were given as suggestions, and the requirement was to speak for approximately five minutes on each of the three main topics. The topics represent different perspectives and high-level constraints for self-referencing each individual's personal experiences. The themes were designed to be presented from the least (introduction) to the highest (socio-emotional life) demand of the high-level constraints. We are confident that these self-referencing tasks are useful given that comparable studies found differences at the individual (Galbusera et al., 2019) and interpersonal levels (Arellano-Véliz et al., 2024a; Paxton & Dale, 2017; Tschacher et al., 2018) using comparable protocols and task lengths. We measured positive and negative affect (state) pre/post the full task

1 Protocol of self-referencing topics available at https://osf.io/ftxgr/

2.4. Quantification and Statistical Analyses

2.4.1. Measurement of Body Motion

Video recordings were analyzed with a behavioral imaging technique to examine frame-by-frame sequences and create body motion patterns (e.g., Paxton & Dale, 2013). The amount of body motion in each video file was calculated using the Motion Energy Analysis software (MEA, version 4.b., Ramseyer 2018, 2020, see also Tschacher et al., 2018). This frame-by-frame differentiation method calculates the change of pixels between each frame of the video recordings. The target area selected to perform the analysis was the full body of each participant recorded at 32 frames per second (fps). The raw time series files were preprocessed within time windows of 0.5 seconds (smoothed) and standardized using the SD (rescaled) (following Kleinbub and Ramseyer, 2021). The data streams were automatically cleaned to remove artifacts and outliers that could result from involuntary changes in the video files due to changes in lighting or otherwise (all missing data and values >10 SD of each time series, as advised by Kleinbub and Ramseyer, 2021), while the laboratory setting provided stable conditions in terms of lighting and no external disturbances. The time series amounted to a final mean of 29.436 data points for the full 15-minute session or 9.743 (SD = 965) data points per participant per topic (on average). We performed central tendency descriptive analyses (for comparative and descriptive purposes) on these cleaned time series such as the average and variability (SD) of body motion and the Recurrence Quantification Analysis (RQA) for all three topics, as detailed below. See Figure 2 with an example of the time series extraction using the MEA software on the video recordings of this study.

Figure 2. Example of Motion Energy Analysis performed on the MEA software

Note: The figure shows an example of the time series generation using the MEA software in one of the video recordings of this study during the individual self-referencing task (Ramseyer, 2018; 2020).

2.4.2 Recurrence Quantification Analysis (RQA)

To quantify dynamic self-organization from the body motion time series, we performed Recurrence Quantification Analysis (RQA) on each participant's motion energy time series and extracted the variables of Determinism, Entropy, Laminarity, and Mean Line (see Table 1 for definitions and introduction for general description of RQA). A recurrence or 'match' in this context refers to a point in the reconstructed phase space where the system returns to a previously visited state (Marwan et al., 2007). This recurrence allows us to identify the self-organizing, recurrent dynamics within the participant's movements. As mentioned in the introduction, the phase space is constructed using embedding dimensions, which transform the time series into a higher-dimensional space where its underlying dynamics can be revealed (Marwan et al., 2007). The embedding process captures hidden relationships and time dependencies in the data that might not be obvious in the original time series. These recurrent states reflect the non-linear, complex patterns characterizing the individual's motor behavior, providing insights into the temporal structure of their actions. Rather than directly representing discrete movements, these recurrences capture dynamic states within the abstract phase space, offering a deeper understanding of how behavior evolves over time as part of a self-organizing system.

In the case of our study, the body motion time series used for RQA were preprocessed, thus smoothed, rescaled, and cleaned (following Kleinbub and Ramseyer, 2021; see 'measurement of body motion' section above). The parameters for the phase state reconstruction lag (or delay) and embedding dimension were set to the values: lag = 40, embedding dimension = 7, using the R packages 'crqa' (Coco et al., 2020), 'nonlinearTseries' (García, 2022), and 'tseriesChaos' (Di Narzo, 2019). To specify the dimensionality of our phase space we calculated the average mutual information for estimating the delay (Abarbanel, 1996), for which the first local minimum is considered to be a good estimate, as this lag is where the time series exhibits more independence of itself (see a tutorial in Wallot & Leonardi, 2018). Similarly, the false-nearest-neighbor procedure was employed for the estimation of embedding parameters, where we searched for a first local minimum in the false-nearest-neighbors analysis (Kennel et al., 1992). The appropriate dimension, that is, the number of surrogate dimensions necessary to unfold the attractor dynamics in the reconstructed phase space, must be selected to reliably treat observations as recurrent (Wallot & Leonardi, 2018). We followed procedures previously described in the literature (e.g., Wallot & Leonardi, 2018; Wijnants et al., 2012) and the procedure employed on a similar time series dataset (Arellano-Véliz et al., 2024a).

Minimum line length (lmin) describes the length of the shortest diagonal line considered in the analysis (Zbilut & Webber, 2006). In our study, it was set to four consecutive recurrences (lmin = 4), which means that deterministic patterns in the behavior should be at least 120 milliseconds (0.12 s, similar to Tommasini et al., 2022).

The default value used in the literature is lmin = 2, but we chose conservative to reduce the number of random structures in diagonal lines in diverse complex systems (e.g., Cox & Van Klaveren, 2024; Thiel et al., 2002; Tommasini et al., 2022; Sviridova & Ikeguchi, 2022). Finally, we used a fixed recurrence rate of 2% as this improves the reliability and comparability of our results across conditions and participants (e.g., Konvalinka et al., 2011; Wijnants et al., 2012; van den Hoorn et al., 2020).

The parameter settings and pre-processing of the data depend on the specific system under study, the nature of the time series, and the software or package utilized. In principle, it may not be necessary to engage in upfront cleaning, smoothing, or rescaling, which can depend on factors like the extent of measurement noise. In our case, since we used motion energy time series, the procedure recommended by Kleinbub and Ramseyer (2021) was followed. In some cases, utilizing the built-in normalizing functions of packages suffices. In general, when conducting RQA, it is necessary to incorporate a norm parameter to re-scale phase spaces concerning the magnitude of their values across different time series, making RQA capable of handling any type of variable (Shockley, 2005; Wallot & Leonardi, 2018). The key objective is to ensure consistency in parameter application across various time series, enabling comparisons across samples or datasets (for a detailed step-by-step protocol consult Wallot & Leonardi, 2018).

Finally, RQA and recurrence plots stand out for their reliance on the sequential organization of the time series under investigation. Unlike the more conventional central tendency measures that aggregate information from the system's behavior (such as mean and SD), RQA retains unique and subtle information about system dynamics (Webber & Zbilut, 2005; Jenkins et al., 2020). This information has demonstrated significance in predicting and understanding human bodily and cognitive functioning (Kunnen, 2012; Paxton & Dale, 2017; Danvers et al., 2021). Nevertheless, to have a more comprehensive overview and also for comparison reasons, we decided to complement the nonlinear (RQA) measures by also computing linear (central tendency) measures such as average (mean) and variability (SD) of the body motion energy time series by each self-referencing topic (see Table 3).

2.5. Multilevel Linear Mixed-Effects Models

Big Five personality traits were associated with dynamic body motion measures (operationalized using RQA) across three self-referencing topics in Maximum Likelihood (ML) linear mixed-effects models (fit using the lme4 R package; Bates et al., 2015). These mixed models had a hierarchical two-level organization in which the results on every topic (level 1, N_1 = 315) were nested into the "participant" structure level where personality traits were situated (level 2, N_2 = 105). Significance and coefficient of determination (R^2) were calculated using Satterthwaite's method to compute the approximate degrees of freedom for t distributions (see lme4 R package for details, Bates et al., 2015). First mixed-effect models were fit to examine differences between the topics (as the independent variable) in terms of system dynamics (four RQA measures each as the outcome of their separate model). Subsequently, we examined the effects of each personality trait on body dynamics separately (and their interaction with topic) to examine trait-specific effects.[2] Third, we estimated a full model with all personality traits cumulatively predicting each RQA measure (in interaction with topic). Overall we fit four full models and estimated 24 model variations to examine the relationship between the big five personality traits and dynamic self-organization of body motion.

Dependent variables in each model were the dynamic self-organization RQA measures (Determinism/Entropy/Mean Line/Laminarity) and the independent variables were the Big Five personality traits (Extraversion, Neuroticism, Conscientiousness, Agreeableness, and Openness to Experience) and the self-referencing topic (a categorical variable with three levels: 1. introduction; 2. bodily perception/sensory life; 3. socio-emotional life), where the introduction topic was considered the baseline in the models.[3]

The models included a random effect (Participant ID) to account for the variation in the response variable that was not accounted for by the fixed effects (i.e., personality traits and topic). All the continuous predictors (personality traits) were centered by their mean and scaled, which involves subtracting the group grand average from each personality score to prevent multicollinearity issues (because of the correlation of predictors) and to improve the interpretability and generalizability of results (this procedure was conducted with the "base" R package, R Core Team, 2022).

*2 The short models are defined following the structure: [Determinism ~ (Neuroticism) * Topic + (1|Participant). One model was performed for each personality trait predicting each RQA measure in interaction with the topic.*
*3 The full mixed effects models are defined following the structure: [Determinism ~ (Neuroticism + Extraversion + Conscientiousness + Agreeableness + Openness to Experience) * Topic + (1|Participant). One model per RQA measure was performed. Consult Bates et al. (2015) to see more detail about the 'lmer' package and model terms.*

2.6. Power and sensitivity

We used some common effect indicators, the coefficient of determination (R2), partial eta squared (n²), correlations (r), and standardized beta weights (ß). We describe coefficients of determination (R^2) as weak if they are between 0.02 and 0.13; moderate between 0.13 and 0.26, and substantial if they are larger than 0.26 (Cohen, 1988). Partial eta squared (n²) was deemed small (0.01), medium (0.06), and large (0.14) (Cohen & Cohen, 1983). Marginal R2 refers to the sample variance explained by fixed effects, conditional R^2 refers to the sample variance explained by both fixed and random effects (Nakagawa, & Schielzeth, 2012). For effect sizes of fixed and random effects, $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$ indicate small, medium, and large effect sizes (Cohen, 1988; Lorah, 2018; f^2 was calculated with 'multilevelTools' R package, Wiley, 2020). Cohen's f^2 assesses the impact of predictors on the variance in the dependent variable. Marginal Cohen's f^2 represents the proportion of variance in the dependent variable explained by fixed effects. Conditional Cohen's f^2 represents the proportion of variance in the dependent variable explained by fixed and random effects, considering the total variance. Correlations (r) and beta's (ß) were deemed small if they fall between 0.10 and 0.19; moderate between 0.20 and 0.29, and large from 0.30 (Peterson & Brown, 2005; Richard et al., 2003). Commonly, for an approximate effect size of r = 0.20 in correlational studies, at least 150 participants are necessary to reduce the errors in estimations (Richard et al., 2003; Schönbrodt & Perugini, 2013). These estimates may be conservative when additional power is derived from individual time series of approximately 29.436 consecutive data points on average per participant (9.743 per topic on average), while we are aware that our sample size is modest. In our study, with a sample of n=105, there was a 0.85 probability of detecting a medium effect size ($f^2 = 0.15$) using a significance level of 0.01. In the full models, we corrected the p-values using the Benjamini-Hochberg (1995) procedure, a modified Bonferroni correction (less conservative) to adjust for alpha inflation related to multiple hypothesis testing (performed with "stats" R Core Team, 2022).

3. Results

3.1. Dynamic Self-Organization by Self-referencing Topics

The descriptive statistics for the variables of interest per task in the laboratory (i.e. conversational topic) and the self-report measures are provided in Tables 3 and 4. There was one missing value in topic 3 for the RQA analysis, which was imputed by the respective group mean (one value among 315 observations). Overall, the means across topics for the RQA measures do not seem to differ substantially, only slightly higher values were observed in topics 2 and 3 (see Table 3).

A repeated measures Analysis of Variance (ANOVA, see Table 3) was performed for each RQA measure separately to test the differences among the three types of topics independent of personality traits (i.e., introduction, bodily perception/sensory life, and socio-emotional life). The results revealed a significant but small effect of topic for Determinism ($F_{(2,208)} = 8.19$, $p < .001$, $\eta^2 = .02$) and Entropy ($F_{(2,208)} = 7.602$, $p < .001$, $\eta^2 = .02$). According to pairwise comparisons (Bonferroni corrected), there were significant differences in Determinism and Entropy between the topics of introduction and bodily perception/sensory life ($p = .03$ and $p = .04$ respectively). These results support the effect of the situation (or conversational topic) on the dynamic self-organization of body motion (H1) but these effects differed between RQA measures as illustrated in the recurrence plots (see Figure 3 for all three self-referencing topics). The same procedure was performed for the linear variables, mean and SD, but no differences were observed (mean body motion: $F_{(2, 208)} = 1.57$, $p = .21$, $\eta^2 = .004$, SD body motion: $F_{(2, 208)} = 1.65$, $p = .20$, $\eta^2 = .02$).

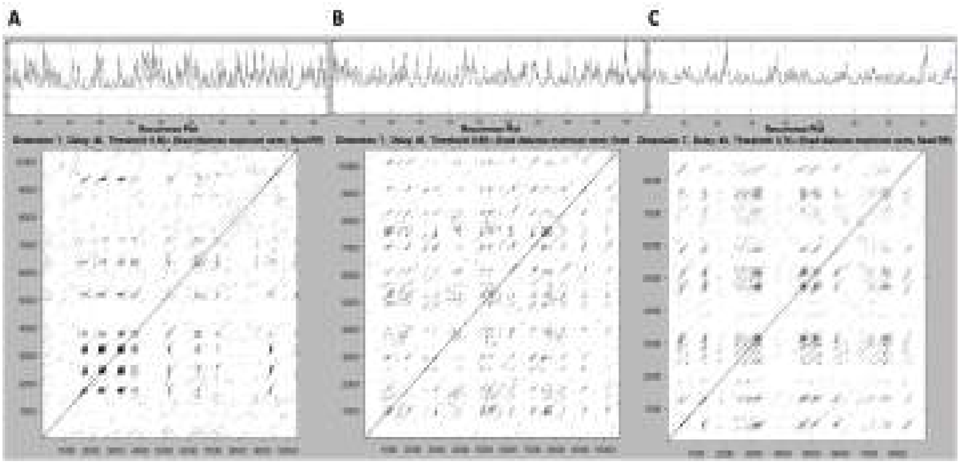
Overall, these findings suggest that the specific self-referencing topic influences their body motions as captured by RQA measures such as Determinism and Entropy. However, the conversational topic effect did not extend to all RQA measures in our study, and did not influence linear measures of mean body motion and the standard deviation of body motion.

Table 3. Descriptive statistics linear and RQA measures of body motion

	Topic 1. Introduction				Topic 2. Bodily Perception/Sensory Life				Topic 3. Socio-emotional Life				ANOVA
Variable	**M**	**SD**	**Mdn**	**Range**	**M**	**SD**	**Mdn**	**Range**	**M**	**SD**	**Mdn**	**Range**	**F**
Average Body Motion	0.73	0.26	0.69	[0.10, 1.37]	0.73	0.25	0.72	[0.07, 1.33]	0.76	0.23	0.79	[0.27, 1.35]	1.57
Variability Body Motion (SD)	0.97	0.16	0.98	[0.17, 1.43]	0.97	0.16	1.00	[0.15, 1.6]	1.01	0.14	0.99	[0.61, 1.63]	1.65
Determinism (DET)	0.90	0.03	0.89	[0.82, 0.98]	0.91	0.03	0.91	[0.82, 0.98]	0.90	0.03	0.91	[0.82, 0.98]	**8.18*** **(T1 < T2)**
Entropy (ENT)	2.87	0.23	2.82	[2.44, 3.44]	2.95	0.23	2.95	[2.4, 3.47]	2.93	0.24	2.92	[2.41, 3,49]	**7.60*** **(T1 < T2)**
Laminarity (LAM)	0.95	0.02	0.95	[0.91, 0.99]	0.96	0.02	0.96	[0.91, 0.99]	0.95	0.02	0.96	[0.91, 0.99]	7.28
Mean Line (ML)	11.40	3.04	10.24	[8.01, 22,74]	12.14	3.04	11.48	[7.73, 25.14]	12.13	3.8	11.12	[7.84, 32.66]	3.47

*Note: N = 105 participants. M = mean, SD = standard deviation, Mdn = median. The degrees of freedom for ANOVA numerators were 2 and for denominator 208, with a within-subject design. Significance at * p < .05 and ** p < .01, and *** p <.000, all Bonferroni corrected.*

Figure 3. Recurrence Plots over the three different self-referencing topics



Note: The figures represent recurrence plots with the respective time series derived from a participant's RQA in three distinct topics (A = Introduction, B = Bodily perception/sensory life, C = Socio-emotional life. The parameters are lag = 40, embedding dimension = 7, lmin = 4, RR = 2%. The main diagonal line goes from down-left to up-right. The x and y axes correspond to the repeated time series at a sample rate of 32 frames per second. Overall, the presence of cluster structures represents regions in phase space repeatedly visited by the system, offering insights into stability, deterministic patterns, transitions, and trajectories. Disruptions in the form of white bands suggest instances of nonstationarity and transitions within the self-referencing task, the variability in the structures represents the dynamical changes of the system (Marwan et al., 2007). The plots were created using the CRP toolbox in Matlab (Marwan, 2013).

Table 4. Descriptive statistics self-report

Variable	Mean	SD	Median	Range
Extraversion	78.07	16.10	80	40-110
Neuroticism	73.91	15.18	73	32-108
Agreeableness	86.21	10.98	87	44-111
Conscientiousness	79.43	15.10	80	44-112
Openness to Experience	89.38	11.00	87	58-115
Positive Affect (pre-task)	13.89	4.35	14	5-23
Positive Affect (post-task)	14.24	4.80	14	5-24
Negative Affect (pre-task)	8.32	3.43	7	5-22
Negative Affect (post-task)	7.68	3.50	6	5-19

Note: N = 105 participants. SD = standard deviation. Pre-task was before starting the laboratory session, and the post-task was after finishing the full 15-minute session.

3.2. Correlation analysis

Pearson correlation coefficients showed positive intercorrelations between all RQA measures (see Table 5). Each RQA and linear body motion measure across the three different topics was combined into a grand average for each measure for each individual to compute the correlations. The correlations between RQA and linear measures of body motion and self-reported personality and affect are provided in Table 5 and show a significant inverse association between overall body motion variability (SD) and the personality traits of Agreeableness ($r = -0.24$), Conscientiousness ($r = -0.20$), and Openness ($r = -0.16$). In other words, the more agreeable, the lower the body motion variability, on average, everything else equal. Agreeable people also reported lower post-task negative affect. Among the RQA measures, more system Laminarity was associated with lower pre-task positive affect ($r = -0.16$).

Personality traits showed inverse correlations such as Neuroticism with Extraversion and Agreeableness, or positive correlations such as between Conscientiousness and Extraversion and Agreeableness, and between Agreeableness and Openness (see Table 5). The Big Five personality factors are defined as independent (orthogonal), nevertheless, these associations are commonly reported, as behavior cannot be clearly divided into absolutely independent categories (Koppensteiner, 2013).

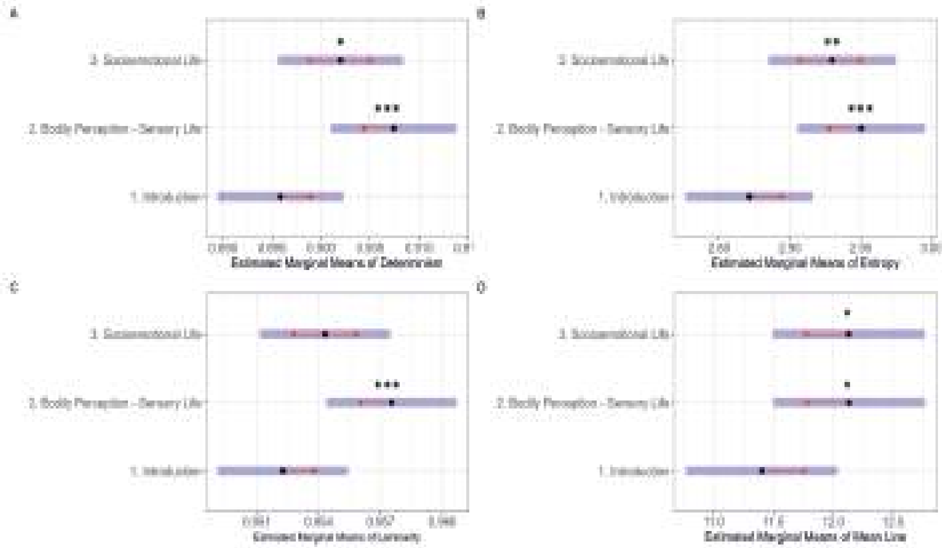
Moreover, higher-order structures (meta-traits) have been reported in the literature (e.g., DeYoung, 2006). In the context of this study, it is possible to indicate, for example, that the effects of Neuroticism (emotional stability) were negatively related to Extraversion and Conscientiousness, to the extent that a highly emotionally stable individual (low Neuroticism) would be likely to score relatively high in Extraversion and Conscientiousness as well (driven by a "maturity" process, see Bleidorn et al., 2022).

3.3. Predicting self-organizing dynamics from personality traits and self-referencing topic

The models estimating the effect of conversational topics on body motion dynamics (Table 6, independent of other predictors) revealed that talking about sensory and social-emotional life (topics 2 and 3) predicted more system Determinism, Entropy, Laminarity, and Mean Line compared to introduction (baseline topic 1, see Figure 4). These results indicate that the psychological situation (in this case, the self-referencing topic) is significantly associated with the dynamic self-organization of body motion in line with our expectations (H1). The Intraclass Correlation Coefficient (ICC) describes the proportion of variance explained by each participant or clustering structure (Hox, 2017), and in this study captures the consistency of the observed effects for each individual across the conversational topics. A larger ICC indicates more consistency in body motion across measurements. The largest ICC (least observed variability across topics) was exhibited in Laminarity (.63), followed by Determinism (.62), Entropy (.58), and Mean Line (.52), which showed the most variability. The differences between the conversational topics (see Figure 4) and especially socioemotional life versus bodily perception suggest that the alternative explanation of our results as reflective of time effects or the sequence of the conversations (e.g., tiredness) has no merit.

Personality and the self-referencing topic explained differences in body motion dynamics (short models), as more extroverted participants showed more Determinism when discussing their bodily perception and/or sensory life (topic 2, $ß = .17$, $p = 0.04$). In this model, higher Extraversion scores were associated with more patterned, consistent, and regular movement dynamics (Determinism) when talking about their bodily perception/sensory life (see Table 7, Figure 5A). Although these results support the higher dynamic self-organization of extroverted individuals (H2a), note that there were no significant effects linked to the other RQA measures, therefore, H2a was only partially met. And, as shown in the plot, this effect of talking about bodily perception/sensory life (topic 2) is qualitatively different from the other topics.

Figure 4. Plots representing the Estimated Marginal Means by Topic



*Note: Estimated Marginal Means from mixed-effects models by each RQA variable (Introduction was considered the baseline). The self-referencing topics were: 1) Introduction, 2) Bodily perception/sensory life, and 3) Socio-emotional life. The central points or markers represent the adjusted means of the response variable for different levels of the predictor variables, accounting for the effects of other variables in the model. The blue bars are confidence intervals for the Estimated Marginal Means, and the red arrows indicate comparisons between the means of the tasks with the baseline task (Introduction). * <. 05, ** < .01, *** < .001*

Neuroticism influenced body motion during the topic about bodily perception/sensory life (topic 2, ß = -.23, $p < .01$) and socio-emotional life (topic 3, ß = -.21, $p < .05$) in terms of system Determinism ($p < .05$, see Table 7) and Laminarity (topic 2, ß = -.23, $p < .05$, see Table 9), and, only when talking about their socio-emotional life (topic 3), in terms of Mean Line (ß = -.19, $p < .05$, see Table 10, Figure 6). These results suggest that higher Neuroticism scores were associated with less patterned or less deterministic processes, less laminar states (more variability, fluctuation, and volatility), and less stability in topics 2 and 3. These results support our hypothesis about less stable, more volatile body motion (self-organizing) dynamics linked to low emotional stability (high Neuroticism) observed across the self-referencing topics (H2b).

Agreeableness showed no association with system states nor any interaction with the topic in any of the individual models thus H2c was not supported.[1] Conscientiousness predicted lower system Determinism (ß =-.21, $p < .05$, Table 7, Figure 5B) and less Laminarity (ß = -.24, $p < .05$, Table 9, Figure 5C) as main effects, but no interaction with the self-referencing topic. More conscientious participants showed less deterministic (patterned), and fewer system laminar states, the inverse of our expectations (H2d, see discussion section), whereas less conscientious participants showed higher Determinism. Openness differences were unrelated to movement dynamics and there was no moderation by topic (thus H2e was not supported). Overall, Neuroticism was the personality trait that evidenced the best fit (in terms of AIC) in the individual models predicting all four RQA measures, and Neuroticism showed the strongest interaction effects with the self-referencing topics.

When performing the full models, we observed personality effects on Determinism (full model, see Table 7, Model 6; estimate = 0.91, $p < .001$), as Determinism was higher when talking about bodily perception/sensory life than when participants introduced themselves. Neuroticism (emotional stability) showed interactions with the topic socio-emotional life (topic 3), particularly, more neurotic participants showed lower Determinism (deterministic patterns) (ß =-.27, $p < .05$), in keeping with the effects observed in the short model of Neuroticism-Determinism, supporting H2b.

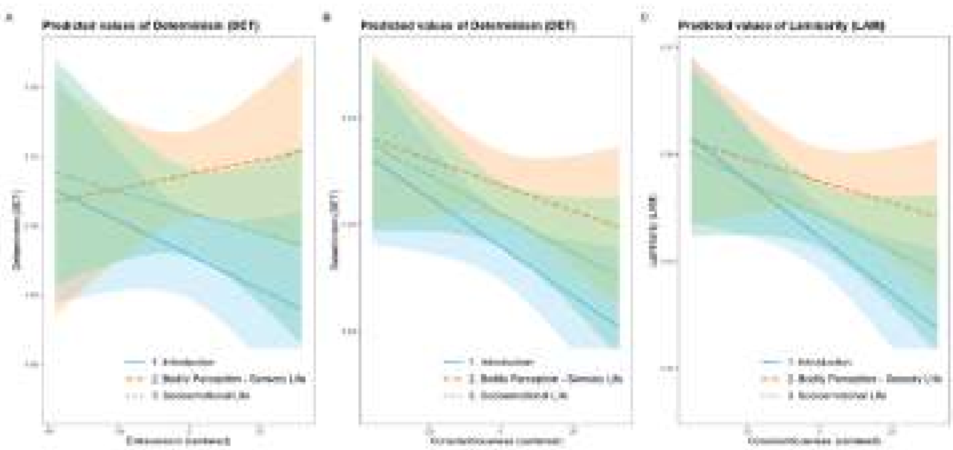
The full model of system Entropy ("complexity", see Table 8, model 6; $p < .001$) showed how self-referencing topics of bodily perception/sensory life and socio-emotional life predicted higher system Entropy compared to the situation in which participants introduced themselves (baseline). More neurotic participants who talked about their socio-emotional life (topic 3) showed lower system Entropy (ß = -.31, $p < .05$) which suggests less complexity in their dynamic self-organization during this particular topic, whereas lower Neuroticism scores (thus emotional stability) predicted more complex motion patterns thus higher Entropy (see Figure 6D), which was in line with expectations (H2b).

During the topic of bodily perception/sensory life (topic 2) participants showed more system Laminarity (see Table 9, model 6, $p < .001$), in support of conversational topics as situational constraints (H1). Finally, in the model of Mean Line (dynamic stability, Table 10), the effect of Neuroticism in interaction with socio-emotional life predicted lower values of Mean Line, which indicates less dynamic stability (ß = -.33, $p < .05$, in line with the expectations (H2b) and the short model estimates. Overall, our results support personality differences in body motion dynamics and their changes across self-referencing topics (H1b). Of the personality factors, only Conscientiousness predicted different body motion dynamics independent of situational constraints (conversational

1 The significant effects in the full model of Entropy (in interaction with topic 2) became non-significant after correcting the p-values; thus, we observed no significant effects on Entropy.

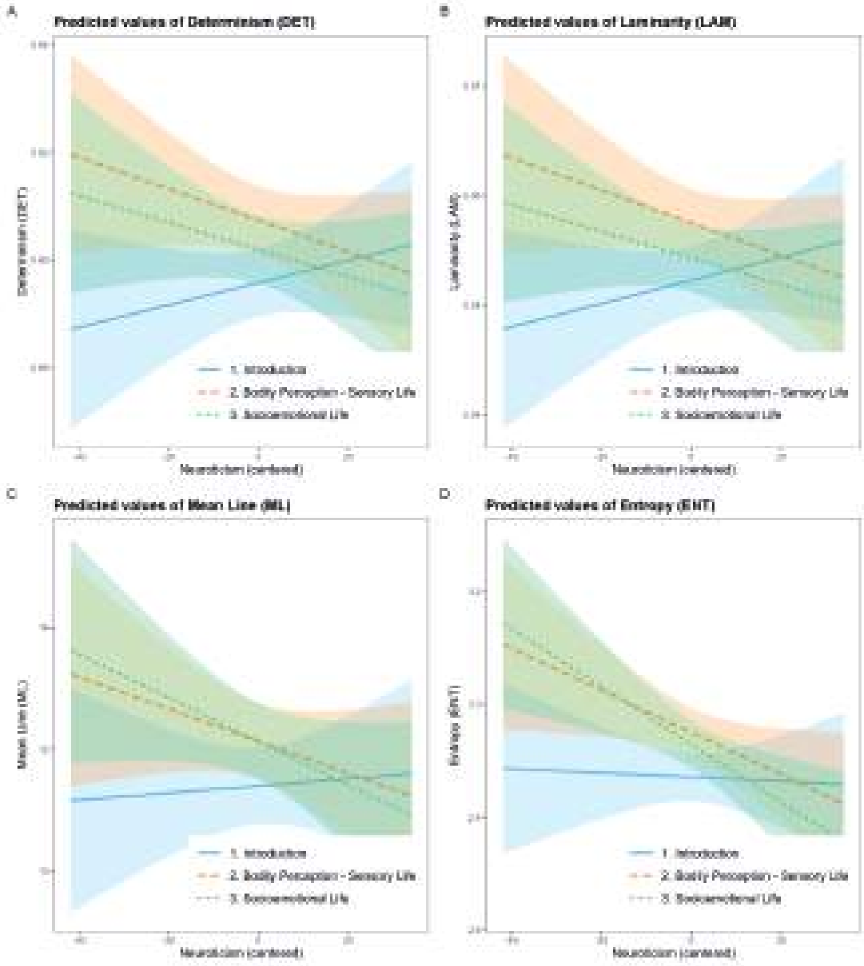
topic), but differences in the other four personality factors influenced how self-referencing topics influenced body motion.

Figure 5. Plots representing significant fixed effects of Extraversion and Conscientiousness on Determinism, and Conscientiousness on Laminarity



*Note: The figures represent the predicted effects in the individual models of (A) Extraversion on Determinism (DET), (B) Conscientiousness on Determinism, and (C) Conscientiousness on Laminarity (LAM). Figure 5A represents the effects of Extraversion on Determinism, in this case, the effect of Extraversion * Topic 2 is statistically significant relative to Topic 1 (baseline). Figures 5B and 5C represent the effects of Conscientiousness on Determinism and Laminarity respectively which resulted in significant results without interacting with the topic. Personality traits were centered.*

Figure 6. Plots representing significant fixed effects of Neuroticism on Determinism, Laminarity, Mean Line, and Entropy



Note: The figures represent the predicted effects of Neuroticism on Determinism (A), Laminarity (B), Mean Line (C) in the individual models; and Neuroticism on Entropy (D) in the full model. Personality traits were centered.

3.4. Affect Valence

Affect valence measures exhibited slightly higher mean values of positive affect post-task and slightly lower negative affect post-task (see Table 4). When testing the report of affect pre and post-task, the ANOVA tests revealed significant differences in negative affect ($F[1,101] = 7.50$, $p = 0.01$, $\eta^2 = 0.07$), but not in positive affect ($F[1,101] = 0.004$, $p = .94$, $\eta^2 = 0.00$) (two observations were removed due to missingness). To explore the effects of personality as predictors of positive and negative affect, general linear models suggested a significant effect of Neuroticism predicting higher negative affect post-task ($p < .001$), in contrast to the effect of Agreeableness, predicting lower negative affect post-task ($p < .001$) (Table 11) (in alignment with H3). This model explains 11% of the variance of negative affect ($R^2 = .11$).

4. Discussion

We studied how personality differences are expressed in body motion dynamics during a conversation using enactive, embodied, and complex systems perspectives. Our study followed two aims: first, exploring the effects of "high-level" situational constraints on body motion dynamics (see introduction section). To accomplish this, we designed a laboratory study in which participants were invited to introduce themselves and talk about their bodily perception/sensory life and their socio-emotional life, and used these three conditions as high-level situational constraints. Second, we explored whether personality differences predicted how these constraints influenced body motion dynamics. Our study yielded two general key observations. First, we established the relevance and explanatory power of subtle high-level situational constraints (such as a self-referencing topic) to understand changes in body motion, indicative of self-organization. Second, we showed how personality differences predicted and moderated the effect of situational constraints on body movement. Both these observations and their implications are discussed in more detail below, followed by the limitations and conclusions of our study.

4.1. Effects of High-Level Constraints on Self-Organization

Darwin (1872) noted how human facial and bodily movements accompanied various emotions and that such body movement dynamics differed as a function of local context and culture. We showed how the type of conversation influenced the body motion of the speaker (in line with H1), especially their Determinism and Entropy (interpreted as complexity, see Table 1). The conversational topics reflect situational constraints that influenced all measures of dynamic self-organization, namely, more Determinism (deterministic patterns), Entropy (complexity), Laminar states, and Mean Line (stability). Apparently, once participants reflected on their bodily and sensory experiences and socio-emotional life, they started to show more organized, complex, stable, and fixated dynamics in their movements (when contrasted to the self-introduction topic). These findings align with the idea that individuals are best understood when immersed in a meaningful environment that promotes flexibility and attunement (Gallagher, 2013; Gallagher & Daly, 2018). In addition, participants reported less negative affect once they completed their study, which could suggest that talking about oneself made people feel better, except for participants with high levels of Neuroticism (low emotional stability).

In our study, the body motion dynamics captured self-organizing processes that are thought to reflect an underlying current of sensations, feelings, thoughts, memories, emotions, and meaning (Gallagher & Daly, 2018; Di Paolo, 2021). The high-level constraints might have created situations that required individuals to attune their systems to changing environmental demands (self-organized criticality, see Goodwin, 2001; Plenz et al., 2021). Our results support conclusions from pioneering studies on the dynamic nature of human systems and their capacity to exhibit emergent self-organized behavior and critical states given specific situational conditions (e.g., Kelso and Schöner, 1988). It is also important to mention that, we interpreted these differences given by the situational constraints as shifts or transitions in the systems' dynamics (e.g., critical states), but this needs to be understood with caution in the context of our aggregated RQA measures across the three self-referencing topics.

4.2. Personality Differences and the Modulation of Self-Organization

Differences in Neuroticism were most predictive of body motion dynamics as high scores (thus low emotional stability) associated with less patterned, unstable, less complex, and more fluctuating/volatile motion dynamics, in line with H2b and the literature (e.g., Mader et al., 2023). These effects were observed when talking about sensory experiences (topic 2) and most pronounced when participants talked about their socio-emotional life (topic 3). Arguably, these self-referencing topics have the potential to promote critical states in the participants and more Neuroticism made state transitions more likely, in line with evidence of heightened sensitivity to environmental demands and more rapid mood changes (e.g., Jeronimus, 2019). Contrarily, low Neuroticism would predict more complex, patterned, and stable dynamics of body motion (high emotional stability, see H2b). These findings on Neuroticism are relevant to the personality literature as the laboratory setting and study methodology allowed us to capture body dynamics (test-data) where Neuroticism differences were more salient than in studies that relied on "observer interpretations" (see Albright et al., 1988; Jiang et al., 2023). These effects may reflect the emotional nature of the self-referencing topics which likely elicited emotion regulation processes (topics 2 and 3, see Robinson et al., 2007), in line with situational personality theories such as the Trait Activation Theory (Tett & Guterman, 2000) and the Whole Trait Theory (Fleeson & Jayawickreme, 2021). Response mechanisms are trait and situation-specific according to the cognitive-affective system theory of personality (Mischel and Shoda, 1995), and although trait expression was not directly measured in our study, our results indicate clear interactions between Neuroticism and situational constraints on body motion dynamics.

As mentioned in the introduction, from an enactive view, personality traits function as stylistic differences in the way that individuals perceive their environments and act toward them (Hovhannisyan & Vervaeke, 2022; Todd & Gigerenzer, 2020; Satchell et al., 2021). Theorists using this approach introduced the dynamic meta-traits Stability and Plasticity in response to the meta-problem of uncertainty referred to as “the variation in the possibilities for action available to the cognitive agent” and it is based on the traditional idea of Entropy described by Shannon (De Young, 2013; Hovhannisyan & Vervaeke, 2022, p.355). Stability accounts for the shared variance of Neuroticism, Agreeableness, and Conscientiousness, whereas Plasticity accounts for the variance of Extraversion and Openness (DeYoung, 2006; DeYoung & Weisberg, 2018). Stability and Plasticity represent adaptive strategies for individuals when confronted with environmental demands or uncertainty (Hovhannisyan & Vervaeke, 2022). This approach adds a dynamic and enactive component to discuss our results.

Neuroticism would optimize organismic security around situational information, perceived threats, or uncertainty (DeYoung, 2013). Phenomenologically, this could be observed in experiencing new situations (uncertain) as threatening and eliciting anxiety and defensive responses; however, this configuration makes individuals better adapted to threats, in opposition to emotionally stable individuals who are less likely to experience new situations as threatening (Hovhannisyan & Vervaeke, 2022; Jeronimus, 2019). Highly neurotic (i.e. emotionally unstable) individuals could have been more nervous or anxious when talking about their sensory and socioemotional experiences (topics 2 and 3), which would align with their body motion patterns and negative affect afterward. Phenomenologically, this instability could reflect a defensive/protective response. Conversely, low neurotic (thus emotionally stable) individuals were unlikely to feel anxious and were more prone to explore (more complex patterns of behavior), and exhibited stability, deterministic patterns, and smoothness in their motion dynamics, which indicates well-adjusted self-organizing dynamics and systemic stability overall (“serenity”).

More extroverted participants showed more regular body motion patterns when talking about their sensory experiences (topic 2), which was contrasted to more irregular patterns during their self-introduction (and when talking about their socio-emotional life but this effect was not significant). Situational constraints influenced body motion dynamics. Without associations between Extraversion and Entropy (interpreted as complexity) H1a received only partial support. Some authors describe a continuum in the affect sphere where bodily and sensorial affects evolve into more complex and stable emotion states (e.g., Barrett, 2017; Newen et al., 2015). Perhaps participants became more self-aware when talking about their bodily perception/sensory life. Extraversion captures sociability (social, gregarious, and outgoing behavior, see McCrae

& Costa, 2003), and our study in which participants were talking alone about themselves may (partly) explain the comparative lack of Extraversion effects (and the presence of Neuroticism effects). Moreover, Extraversion focuses attention on the reward value of uncertainty (dopaminergic processes), which promotes exploration behavior in response to perceived uncertainty (DeYoung 2013; Hovhannisyan & Vervaeke, 2022). Such processes could explain why highly extroverted individuals responded to conversations about bodily perception/sensory life but no other effects were observed (such as Entropy). Possibly, the situation may have not been stimulating enough given the high sensation threshold characteristic of extroverted individuals. In addition, the individual (instead of social) and concrete (bodily-oriented) theme may not be relevant to see further effects (which needs to be tested with a larger sample to address any potential power issues).

More conscientious participants showed lower Determinism and Laminarity (contrary to H2d), but no differences in body motion between conversational topics, which suggests reduced sensitivity to (high-level) contextual constraints, and more behavioral stability regardless of the situation. Conscientiousness is a personality factor associated with self-discipline, organization, goal-directed behavior, attention to detail (McCrae, 2004), eagerness to follow rules, and prioritizing long-term goals via motivation, industriousness, and focus (DeYoung, 2015; DeYoung & Weisberg, 2018).

We expected that more conscientious participants would show more Determinism and Laminarity in their body motion dynamics (H2d) but our results suggest that Conscientiousness primarily reflects differences in detail orientation and adaptability (Ness et al., 2021). Conscientious individuals indeed tend to pay attention to subtle nuances in their movement –as they may prioritize goal achievement according to situational affordances, directing their attention toward the stimuli that are relevant to their goal (e.g., Sassenberg et al., 2023). Likewise, body motion may be optimized to perform during the experiment, leading to less deterministic (less regular/patterned), more variable (less laminar states), and possibly, efficient dynamics. Thus, individuals who score high in Conscientiousness seemed to display more varied and less stereotypical movement patterns. It remains an open question why conscientious participants tend to show these self-organizing embodied dynamics (i.e. the driving “mechanisms”).

According to the high-performance cycle of goal-setting theory (Locke & Latham, 2002; 2019), the specificities and difficulty of a topic are related to the use of mechanisms of attention, effort, persistence, and strategy. These mechanisms would lead to high performance, satisfaction, and reward; and all of them are predictive of high Conscientiousness (Bates et al., 2023). These mechanisms suggest that highly conscientious individuals may have paid more attention during the task. However, it is necessary to understand how personality trait interactions across situations influence embodied and self-organizing dynamics, for instance, highly conscientious-extroverted individuals compared to conscientious-introverted ones. In this regard, facets of Conscientiousness can be relevant, industriousness (relevant for goal achieving) is negatively related to Neuroticism and positively related to Extraversion (higher reward sensitivity, Hovhannisyan & Vervaeke, 2022). Orderliness, characterized by reducing distractions, is positively related to Neuroticism and negatively related to Extraversion (Rueter, 2018; Hovhannisyan & Vervaeke, 2022). These interactions may signify different mechanisms for situational demands, crucial for future research. For example, a conscientious person with a highly "industrious" component (low Neuroticism/high Extraversion) might exhibit higher Entropy, variability, and flexible patterns compared to a more orderliness-oriented individual (high Neuroticism/low Extraversion), even though both are highly conscientious. Exploring interactive effects among RQA measures (e.g., interactions with Entropy, Laminarity, or Mean Line) is also pertinent for understanding further system dynamics.

Differences in Agreeableness and Openness were not associated with differences in body motion dynamics (H2c was not supported). More agreeable participants reported less negative affect after the task, which may reflect their characteristic cooperation, compassion, warmth, politeness, transparency, and communion (McCrae & Costa, 2003). Zooming into some of these characteristics, politeness has been described as a voluntary, conscious process and selective constraint toward pro-social possibilities (Hovhannisyan & Vervaeke, 2022); and communion refers to a person's wish to relate closely, merge, cooperate with others, and express their own emotions (Bakan, 1966; Abele & Wojciszke, 2007). Perhaps agreeable individuals felt less negative affect after disclosing personal information, such as, about their families and friends. Prior research has shown that communion is linked to taking others' perspectives when sharing information (Abele & Wojciszke, 2007). Nevertheless, the content of the participants' speech was not studied, and it would be relevant to incorporate in future research.

The absence of effects for Openness can be explained by the laboratory task. According to a study that reviewed methods that promote the expression and perception of personality traits (Wrzus & Mehl, 2015), the ideal situations to capture effects related to Openness should promote creativity and imagination, as well as involve new experiences. These situations can provide space to display behavioral plasticity and complex behavior. Hence, it is likely that the scenario of our study and the body motion measurement were suboptimal to study Openness to experience. In addition, the effect sizes were small in general, which can be also a reason to consider a larger sample size to detect such effects.

Finally, as mentioned in the introduction, complex adaptive systems, like humans, are thought to gravitate towards a dynamic equilibrium, while constantly attuning satisfactorily to the ever-changing immediate environment (e.g., López-Ruiz et al., 1995; Chemero, 2003; Bruineberg et al., 2019). In the context of our study, to address the problem of uncertainty –described by enactive theories–, we believe that when individuals were confronted with task-induced uncertainty (high-level constraints), they exhibited dynamical attunement. This process is reflected in the balance of flexibility and stability, indicated by the measure of Entropy (cf. Cox & Van Klaveren, 2024) while maintaining degrees of stability, reflected in measures like Determinism, Laminarity, and Mean Line. It is crucial to remember that complexity encompasses adaptive mechanisms that reflect the system's flexibility (e.g., perform exploratory behaviors), and the ability to attune and be responsive to their environments, fluctuating towards critical states, and sustain stability. Consequently, it is relevant to study these dynamics and interactive effects between RQA measures (e.g., the interplay between Determinism, Entropy, Laminarity, and Mean Line) at different time scales and across situations.

5. Conclusions, Limitations, and Future Directions

This paper showed how embodied, enactive, and complex systems perspectives can be used to examine personality theories and situational effects on body motion dynamics. Our results underscore that personality is embodied and illustrate the role of situational constraints using methodology from complexity science. Future studies may enrich our understanding of how various levels of phenomenology from body machinery to first-person experiences are interwoven. Also, the study of mechanisms involved in dynamic self-organization seems a fruitful avenue.

Our study and interpretations are limited by the modest sample size and generalizability as our sample was composed primarily of female undergraduate students, from which a relevant part corresponds to "western, educated, industrialized, rich, and democratic societies" (Henrich et al., 2010). In addition, the laboratory task involved the presence of an experimenter, even though we followed a rigorous protocol. We employed a self-report questionnaire to measure personality traits cross-sectionally, which might not be optimal from a complex dynamic systems perspective as we could not consider the dynamic features of these traits/states over time. However, we acknowledge the functionality of our assessment tools, their psychometric properties, and the rigorous scientific work behind their development. Although the RQA is a powerful tool to study patterns in a time series it does not describe underlying mechanisms and the high correlations between RQA measures must be addressed in future studies by using a supervised machine learning analysis such as principal components procedure. Besides, it would also be relevant to study the interactive effects of these variables while accounting for their inter-correlations. More research is needed to define thresholds and parameters in RQA that apply to specific systems or levels of explanation. This would be necessary to fully integrate these measurements in the context of psychological constructs. In this sense, adopting multimodal and multimethod approaches is advised in general. Finally, given the structure of our task (intentionally from least to highest demand of the high-level constraints), we did not randomize the order of the tasks, nor could report the presence of any fatigue-related effects. However, we designed a task that could efficiently provide the relevant information without being extensive or unnecessarily exhausting.

6. Acknowledgments

We thank all participants of the study. We acknowledge Mark Span (Ph.D.) for technical support on the experimental setup. Nicol Arellano-Véliz was supported by Agencia Nacional de Investigación y Desarrollo (ANID), Gobierno de Chile (Ph.D. Scholarship 72200122), Bertus Jeronimus by NWO-Veni 016.195.405. Ramón Castillo was supported by ANID, Gobierno de Chile (FOVI210047; FONDEQUIP-EQM 190153) and Programa de Investigación Asociativa en Ciencias Cognitivas (RU-158-2019), Universidad de Talca, Chile.

7. Ethics statement and conflict of interest

This study was approved by the Ethical Committee for research with human participants of the Faculty of Behavioural and Social Sciences, University of Groningen, code PSY-1920-S-0525. The authors declare no conflict of interest related to this research, authorship, or publication.

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10. Data availability

Further materials such as data and scripts can be accessed at https://doi. org/10.17605/OSF.IO/FTXGR and pre-registration at https://doi.org/10.17605/OSF.IO/ PCVBT

Table 5. Pearson correlations (r) between body motion variables (grand average) and self-report protocols

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Extraversion	–													
2. Neuroticism	**-0.50***													
3. Agreeableness	**0.24***	**-0.23***												
4. Conscientiousness	**0.24***	-0.25	**0.30***											
5. Openness	0.28	0.07	**0.33***	0.13										
6. Determinism (DET)	-0.06	-0.06	-0.01	-0.19	0.14									
7. Entropy (ENT)	-0.07	-0.08	0.01	-0.15	0.11	**0.95***								
8. Laminarity (LAM)	-0.08	-0.06	-0.02	-0.19	0.09	**0.97***	**0.90***							
9. Mean Line (ML)	-0.05	-0.10	0.01	-0.11	0.14	**0.86***	**0.89***	**0.81***						
10. Average body motion	0.02	-0.03	-0.10	-0.16	-0.01	-0.02	-0.06	-0.07	0.02					
11. Variability (SD) body motion	-0.18	0.13	**-0.24***	**-0.20***	**-0.16***	0.05	0.06	0.05	0.06	**0.35***				
12. PA Pre-task	0.21	-0.06	0.10	0.11	0.17	-0.11	-0.07	**-0.16***	-0.07	0.17	0.16			
13. PA. Post-task	0.02	-0.10	0.05	0.00	0.00	-0.07	-0.07	-0.10	-0.04	0.22	-0.10	-0.01		
14. NA. Pre-task	-0.03	0.10	0.01	0.06	-0.06	0.07	0.07	0.04	0.11	-0.17	0.00	-0.01	0.02	
15. NA. Post-task	-0.01	0.21	**-0.23***	0.00	0.04	0.05	0.02	0.06	0.05	0.02	0.11	0.05	**-0.24***	0.26

*Note: N = 105 participants, 315 observations. Significance was indicated as * p < .05. ** p < .01,***p <.001.The body motion variables (linear and nonlinear) correspond to the full task (grand average of the three topics). NA = Negative Affect (state). P.A. = Positive affect (state). SD = Standard Deviation. All dynamic system measures (6-9) are defined in Table 1.*

Table 6. Mixed-Effects Models predicting RQA measures from self-referencing topics with 105 participants (N_i) and 315 observations (N_t), (105i * 3 topics)

	M1. Determinism	M2. Entropy	M3. Laminarity	M4. Mean Line
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Intercept	**.90(-.18)*** **	**2.87(-.19)*** **	**0.95(-.15)*** **	**11.40(-.15)*** **
Topic 2 (T.2)	**.001(.35)*** **	**.08(.34)*** **	**.005(.32)*** **	**.73(.22)***
Topic 3 (T.3)	**.001(.18)***	**.06(.25)** **	.002(.12)	**.73(.22)***
Random Effects				
ICC	.61	.57	.62	.51
Marg. R^2/Cond. R^2	.02 / .62	.02 / .58	.02/.63	.01/.52
AIC	-1357	-113.5	**-1808.2**	1578.7
Effect size (f^2) (marg/cond)	.02/1.63	.02/1.39	.02/1.70	.02/1.06

*Note: Significance was indicated as * p < .05. ** p < .01,***p <.001. N_i = number of participants. N_t = total; number of observations, which was = 315 (105 participants * 3 topics). SE = Standard Error. T.2 = Topic 2, a self–referencing speaking task about bodily perception/sensory life; T.3 = Topic 3, a self–referencing speaking task about socio-emotional life. AIC = Akaike's Information Criterion (lower values indicate better fit). ICC = Intra-class Correlation Coefficient; marg=marginal (fixed effects), cond =conditional (fixed and random effects). M1.= dynamic system measure 1, Determinism, see Table 1 for definitions. ß = standardized beta weights.*

Table 7. Mixed-Effects Models predicting Determinism. N_i = 105; N_t = 315 observations (105i * 3 topics)

	Model 1. Extraversion	Model 2. Neuroticism	Model 3. Agreeableness	Model 4. Conscientiousness	Model 5. Openness	Model 6. Full model
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Intercept	**.90(-.18)*** **	**.90(-.18)*** **	**.90(-.18)*** **	**.90(-.18)*** **	**.90(-.18)*** **	**.91(-.18)*** **
Extraversion	-.004(-.12)					-.004(-.12)
Neuroticism		.003(.09)				-.001(-.03)
Agreeableness			-.001(-.02)			.006(.02)
Conscient.				**-.007(-.21)***		-.007(-.21)
Openness					.003(.09)	.005(.14)
Topic 2 (T.2)	**.001(.35)*** **	**.012(.35)*** **	**.001(.35)*** **	**.012(.35)*** **	**.012(.35)*** **	**.022(.35)*** **
Topic 3 (T.3)	**.006(.18)***	**.006(.18)***	**.006(.18)***	**.006(.18)***	**.006(.18)***	.006(.18)
Extraversion*T.2	**.006(.17)***					.001(.04)
Extraversion*T.3	.002(.05)					-.004(-.11)
Neuroticism*T.2		**-.008(-.23)*** **				-.007(-.22)
Neuroticism*T.3		**-.007(-.21)***				**-.009(-.27)***
Agreeableness*T.2			-.000(-.00)			-.004(-.11)
Agreeableness*T.3			.001(.04)			-.001(-.02)
Conscient.*T.2				.003(.10)		.002(.05)

Table 7. Mixed-Effects Models predicting Determinism. N_i = 105; N_t = 315 observations (105i * 3 topics) (continued)

	Model 1. Extraversion	Model 2. Neuroticism	Model 3. Agreeableness	Model 4. Conscientiousness	Model 5. Openness	Model 6. Full model
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Conscient.*T.3				.001(.04)		-.000(-.00)
Openness*T.2					.002(.07)	.003(.10)
Openness*T.3					.001(.03)	.003/(.09)
Random Effects						
ICC	.62	.62	.61	.60	.61	.60
Marg. R^2/Cond. R^2	.03 / 0.64	.03 / .64	.02 / .62	.05 / .62	.03 / .62	0.11 / 0.64
AIC	-1355.6	**-1360.3**	-1351.4	-1356.2	-1353.8	-1352
Effect size (f2) (marg/cond)	.03/1.68	.03/1.74	.02/1.63	.05/1.65	.04/1.64	0.12/1.81

*Note: Significance was indicated as * p < .05. ** p < .01,***p <.001. p-values were corrected in the full model by Benjamini-Hochberg procedure (1995). T2 = Topic 2, bodily perception/sensory life; T3 = Task 3, socio-emotional life. Conscient. = Conscientiousness. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit); marg=marginal (fixed effects), cond =conditional (fixed and random effects). Personality traits were centered and scaled. ß = standardized beta weights.*

Table 8. Mixed-Effects Models predicting Entropy. Ni = 105; Nt = 315 observations (105i * 3 topics)

	Model 1. Extraversion	Model 2. Neuroticism	Model 3. Agreeableness	Model 4. Conscientiousness	Model 5. Openness	Model 6. Full model
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Intercept	**2.87(-.19)***	**2.87(-.19)***	**2.87(-.19)***	**2.87(-.19)***	**2.87(-.19)***	**2.87(-.19)***
Extraversion	-.017(-.07)					-.020(-.09)
Neuroticism		.001(.04)				-.006(-.02)
Agreeableness			.015(.06)			.025(.11)
Conscientiousness				-.034(-.14)		-.004(-.17)
Openness					.012(.05)	.015(.06)
Topic 2 (T.2)	**.079(.34)***	**.079(.34)***	**.079(.34)***	**.079(.34)***	**.079(.34)***	**.079(.34)**
Topic 3 (T.3)	**.059(.25)**	**.059(.25)**	**.059(.25)**	**.059(.25)**	**.059(.25)**	**.059(.25)***
Extraversion* T.2	.026(.11)					-.001(-.00)
Extraversion * T.3	-.013(-.06)					-.051(-.22)
Neuroticism * T.2		-.003(-.17)				-.051(-.22)
Neuroticism * T.3		-.002(-.15)				**-.072(-.31)***
Agreeableness* T.2			-.020(-.09)			-.047(-.20)
Agreeableness* T.3			-.018(-.08)			-.034(-.14)
Conscient.* T.2				.058(.06)		.012(.05)
Conscient.* T.3				-.003(-.01)		-.003(-.01)

Table 8. Mixed-Effects Models predicting Entropy. Ni = 105; Nt = 315 observations (105i * 3 topics) (continued)

	Model 1. Extraversion	**Model 2. Neuroticism**	**Model 3. Agreeableness**	**Model 4. Conscientiousness**	**Model 5. Openness**	**Model 6. Full model**
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Openness * T.2					.019(.08)	.036(.15)
Openness* T.3					.008(.03)	.039(.16)
Random Effects						
ICC	.58	.58	.58	.57	.57	.57
Marg. R^2/Cond. R^2	.02 / .59	.03 / .59	.02 / .58	.04 / 58	.03 / .58	.09 / .61
AIC	-111.7	**-112.6**	-108.7	-110.8	-109.5	-108.3
Effect size (f^2) (marg/cond)	.03/1.44	.03/1.44	.02/1.41	.04/1.40	.03/1.40	0.11/1.58

*Note: Significance was indicated as * p < .05. ** p < .01,***p <.001. p-values were corrected in the full model by Benjamini-Hochberg procedure (1995). T.2 = Topic 2, bodily perception/sensory life; T.3 = Topic 3, socio-emotional life. Conscient. = Conscientiousness. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit); marg=marginal (fixed effects), cond =conditional (fixed and random effects). Personality traits were centered and scaled. ß = standardized beta weights.*

Table 9. Mixed-Effects Models predicting Laminarity. Ni = 105; Nt = 315 observations (105i * 3 topics)

	Model 1 Extraversion	Model 2 Neuroticism	Model 3 Agreeableness	Model 4 Conscientiousness	Model 5 Openness	Model 6 Full model
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Intercept	**.95(-.15)*** **	**.95(-.15)*** **	**.95(-.15)*** **	**.95(-.15)*** **	**.95(-.15)*** **	**.95(-.15)*** **
Extraversion	-.002(-.13)					-.190(-.12)
Neuroticism		.002(.10)				-.000(-.02)
Agreeableness			-.001(-.05)			.000(.01)
Conscientiousness				**-.004(-.24)***		-.004(-.23)
Openness					.000(.03)	.002(.09)
Topic 2 (T2)	**.005(.32)*** **	**.005(.32)*** **	**.005(.32)*** **	**.005(.32)*** **	**.005(.32)*** **	**.005(.32)** **
Topic 3 (T3)	.002(.12)	.002(.12)	.002(.12)	.002(.12)	.002(.12)	.002(.12)
Extraversion* T.2	.002(.15)					-.000(-.01)
Extraversion * T.3	.001(.06)					-.173(-.10)
Neuroticism * T.2		**-.004(-.23)** **				-.004(-.24)
Neuroticism * T.3		**-.003(-.21)***				-.004(-.26)
Agreeableness* T.2			.001(.04)			-.001(-.08)

Table 9. Mixed-Effects Models predicting Laminarity. Ni = 105; Nt = 315 observations (105i * 3 topics) (continued)

	Model 1 Extraversion	Model 2 Neuroticism	Model 3 Agreeableness	Model 4 Conscientiousness	Model 5 Openness	Model 6 Full model
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Agreeableness* T.3			.001(.09)			.000(.01)
Conscient.* T.2				.002(.15)		.002(.10)
Conscient.* T.3				.001(.09)		.001(.03)
Openness * T.2					.000(.09)	.002(.12)
Openness* T.3					.000(.06)	.002(.10)
Random Effects						
ICC	.63	.63	.62	.62	.62	.62
Marg. R2/Cond. R2	.03 / .64	.03 / .64	.02 / .63	.05 / .63	.03 / .63	.08 / .65
AIC	-1805.9	**-1812.1**	-1803.3	-1809.1	-1804.3	-1802.1
Effect size (f2) (marg/cond)	.03/1.74	.03/1.82	.02/1.71	.05/1.74	.03/1.71	.11/1.89

*Note: Significance was indicated as * p < .05. ** p < .01,***p <.001. p-values were corrected in the full model by Benjamini-Hochberg procedure (1995). T.2 = Topic 2, bodily perception/sensory life; T.3 = Topic 3, socio-emotional life. Conscient. = Conscientiousness. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit); marg=marginal (fixed effects), cond =conditional (fixed and random effects). Personality traits were centered and scaled. ß= standardized beta weights.*

Table 10. Mixed-Effects Models predicting Mean Line. Ni = 105; Nt = 315 observations (105i * 3 topics)

	Model 1. Extraversion	Model 2. Neuroticism	Model 3. Agreeableness	Model 4. Conscientiousness	Model 5. Openness	Model 6. Full model
Predictors	Estimate (ß)	Estimate (ß)	Estimate (ß)	Estimate (ß)	Estimate (ß)	Estimate (ß)
Intercept	**11.40(-.15)*** **	**11.40(-.15)*** **	**11.40(-.15)*** **	**11.40(-.15)*** **	**11.40(-.15)*** **	**11.40(-.15)*** **
Extraversion	-.219(-.07)					-.346(-.10)
Neuroticism		.089(.03)				-.202(-.06)
Agreeableness			-.030(-.01)			-.027(-.01)
Conscientiousness				-.328(-.10)		-.342(-.10)
Openness					.249(.08)	.413(.12)
Topic 2 (T2)	**.731(.22)***	**.731(.22)***	**.731(.22)***	**.731(.22)***	**.731(.22)***	.731(.22)
Topic 3 (T3)	**.728(.22)***	**.728(.22)***	**.728(.22)***	**.728(.22)***	**.728(.22)***	.728(.22)
Extraversion* T.2	.355(.11)					.058(.02)
Extraversion * T.3	-.048(-.01)					-.675(-.20)
Neuroticism * T.2		-.489(-.15)				-.493(-.15)
Neuroticism * T.3		**-.631(-.19)***				**-1.089(-.33)***
Agreeableness* T.2			.095(.03)			-.124(-.04)
Agreeableness* T.3			.114(.03)			-.093(-.03)
Conscient.* T.2				.175(.05)		.043(.01)
Conscient.* T.3				-.086(-.03)		-.245(-.07)

Table 10. Mixed-Effects Models predicting Mean Line. Ni = 105; Nt = 315 observations (105i * 3 topics) (continued)

	Model 1. Extraversion	Model 2. Neuroticism	Model 3. Agreeableness	Model 4. Conscientiousness	Model 5. Openness	Model 6. Full model
Predictors	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**	**Estimate (ß)**
Openness * T.2					.197(.06)	.248(.07)
Openness* T.3					.269(.08)	.592(.18)
Random Effects						
ICC	.51	.51	.51	.51	.50	.50
Marg. R2/Cond. R2	.02 / .52	.03 / .53	.02 / .52	.02 / .52	.03 / .52	.09 / .54
AIC	1582.6	**1579.2**	1584.6	1582.7	1581.6	1587.3
Effect size (f2) (marg/cond)	.02/1.08	.03/1.11	.01/1.06	.02/1.07	0.03/1.07	.10/1.17

*Note: Significance was indicated as * p < .05. ** p < .01,***p <.001. p-values were corrected in the full model by Benjamini-Hochberg procedure (1995). T2 = Topic 2, bodily perception/sensory life; T3 = Topic 3, socio-emotional life. Conscient. = Conscientiousness. M1= Model 1. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit); marg=marginal (fixed effects), cond =conditional (fixed and random effects). Personality traits were centered and scaled. ß = standardized beta weights.*

Table 11. General Linear Models predicting affect valence from Personality (N = 103)

	M1. Positive Affect Pre-Task	M2. Positive Affect Post-Task	M3. Negative Affect Pre-Task	M4. Negative Affect Post-Task
Predictors	Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
Intercept	**13.88 (0.43)*****	**14.23 (0.48)*****	**8.32 (0.34)*****	**7.69 (0.33)*****
Extraversion	0.80 (0.53)	-0.23 (0.60)	0.20 (0.42)	0.42 (0.41)
Neuroticism	0.17 (0.53)	-0.57 (0.60)	0.57 (0.42)	**0.82 (0.41)***
Agreeableness	0.08 (0.48)	0.17 (0.54)	0.17 (0.38)	**-0.88 (0.38)***
Conscientiousness	0.24 (0.46)	-0.11 (0.52)	0.28 (0.37)	0.34 (0.36)
Openness	0.44 (0.48)	0.05 (0.55)	-0.39 (0.39)	0.21 (0.38)
R^2	.06	.02	.03	.11

*Note: Significance was indicated as * p < .05. ** p < .01,***p <.001. Number of observations = 103 (two missing values). Predictors are centered and scaled. M1= Model 1. SE= Standard error.*

Chapter 5

Beyond Words: Speech Synchronization and Conversation Dynamics Linked to Personality and Appraisals

Submitted and Pre-Print Available as:

Arellano-Véliz, N. A., Castillo, R. D., Jeronimus, B. F., Kunnen, E. S., & Cox, R. F. A. (2024). Beyond words: speech synchronization and conversation dynamics linked to personality and appraisals (under review). Preprint available at Research Square: https://doi.org/10.21203/rs.3.rs-4144982/v1

Abstract

We studied how personality differences and conversation topics predict interpersonal speech synchronization, leading/following dynamics, and nonverbal interactional dominance in dyadic conversations. 100 undergraduate students (50 same-gender dyads) had a 15-minute conversation following three topics (introduction/self-disclosure/argumentation) in our laboratory. Their speech synchronization and turn-taking (speech/silence) dynamics were assessed through nonlinear time-series analyses: Cross-Recurrence Quantification Analysis (CRQA), Diagonal Cross-Recurrence Profiles (DCRP), and Anisotropic-CRQA. From the time series, we extracted five variables to operationalize speech synchronization (global and at lag-zero), leading-following dynamics, and asymmetries in the interacting partners' nonverbal interactional dominance. Interaction appraisals were also assessed. Associations between personality traits Extraversion/Agreeableness, speech synchronization, and nonverbal interactional dominance were tested using mixed-effects models. Speech synchronization and nonverbal interactional dominance differed across conversational topics and peaked during argumentative conversations. Extraversion was associated with increased speech synchronization, and nonverbal interactional dominance, especially during an argumentative conversation. Extraversion homogeneity was associated with more symmetry in turn-taking dynamics during a self-disclosure conversation. Speech synchronization was generally associated with positive post-conversational appraisals, such as wanting to meet in the future or liking the conversation partner, particularly among extroverted individuals. In contrast, introverts seemed to value swift conversational dynamics to a lesser extent. High Agreeableness predicted less speech synchronization during argumentative conversations, and increased speech synchronization (at lag-zero) predicted reduced perceived naturality in agreeable individuals. This may suggest a trade-off between maintaining swift speech dynamics and the natural flow of conversation for individuals high in Agreeableness.

Keywords: interpersonal coordination, synchrony, dyadic interactions, personality, speech coordination, speech synchrony

1. Introduction

The course and dynamics of a conversation between two partners (a dyad) and how they experience the interaction are affected by contextual factors (i.e., situations) and individual differences (e.g., personality traits, see Harley, 2013). Interpersonal speech dynamics such as the temporal attunement of speech and silence turns show how dyads synchronize during conversations (through turn-taking dynamics), the leading-following dynamics they exhibit, and how potential nonverbal interactional dominance asymmetries emerge from the mutual influence of interacting partners. We present a study with four aims. First, we use complex dynamical systems theory and speech recordings during conversations to quantify differences in overall speech synchronization through turn-taking behaviors, leader-follower dynamics (temporal domain), and differences or asymmetries in nonverbal interactional dominance between the interaction partners (e.g., one person tends to "dominate" the conversation to a greater extent through speech or silence episodes). Second, we examine whether these speech dynamics differ across three types of conversations, introduction, self-disclosure, and an argumentative conversation. Third, we examine how dyadic speech dynamics differ as a consequence of their personality traits, and study dyadic combinations (one or both low/high scores) of Extraversion (sociability) and Agreeableness (nurturance). Fourth, we examine how interpersonal speech synchronization and personality traits influence how both interacting partners appraise their conversation in terms of the perceived quality of the interaction and rapport. We conclude by discussing our study results and their fit in the broader literature of interaction and personality theory.

1.1. Interpersonal Speech Dynamics

Human communication extends beyond spoken words and comprises a complex flow of interpersonal dynamics within conversations. Language, viewed as a complex adaptive system, operates through a set of interacting elements distributed across the body and social environments (Ellis & Larsen-Freeman, 2009; Di Paolo et al., 2018; Lund et al., 2022). These language elements modulate perceptions, emotions, and thoughts, and convert these experiences into meaningful language expressions (Scheidt et al., 2021). In this way, the behavior of each interacting partner is influenced by characteristic adaptations –i.e., perceptual information, situations, social motivations, and other individual differences (Asendorpf, 2017; Beckner et al. 2009; Mischel & Shoda, 2005), such as gaze, gestures, movement, and speech synchronization (Fusaroli et al., 2014). Recognizing language as a complex adaptive system has implications for interpersonal settings when interacting partners are connected via verbal and nonverbal communication (Thibault, 2004; Falandays et al., 2018; Scheidt et al., 2021). These joint dynamics emerge in dyadic interactions where both partners shape the unfolding conversation (Reuzel et al., 2013), and dyads constitute the majority of human social interactions (Peperkoorn et al., 2020).

People mutually adjust in a conversation in terms of turn-taking, pauses, speech duration, speech rate, response latency, vocal intensity, and movement, among others, which synchronize across timescales (Fowler et al., 2008; Reuzel et al., 2014; Bloomfield et al., 2021). Such interpersonal speech dynamics are key to this study in which we focus on speech synchronization through turn-taking behaviors, the presence of leader-follower dynamics, the differences or asymmetries in nonverbal interactional dominance between the interaction partners; as well as individual differences in the personality traits Extraversion and Agreeableness in these conversation dynamics.

1.1.1. Functional Synchronization in Social Interactions

Speech synchronization can be described in terms of self-organized sets of coupled components that behave as a single functional unit –such as a conversation (Bernieri et al., 1988; Shockley et al., 2009). Such sets of components are self-organized and context-sensitive because each individual actively structures exchanges with the environment to generate and maintain systemic stability (Varela et al., 1991, 2017). In this way, interacting partners develop stable interaction patterns that are softly assembled (context-sensitive), self-organized, and adapted to reap their opportunities (or affordances) and goals in specific situations, whether those motives are affiliative, competitive, or problem-solving, among others (Fusaroli et al., 2014; Kelso et al., 1984; Shockley et al., 2003). In essence, the actions of one member of the dyad impact the actions of the other as they start behaving as a coupled system (Shockley et al., 2009).

In the context of our study, speech synchronization refers to interdependent dynamics among conversational elements (speech and silence turns) that exhibit coherence and are coupled over time. Speech synchronization does not necessarily mean that interacting partners show the same action simultaneously as co-occurring states, but involves compensatory dynamics that allow for the emergence of functions to achieve specific goals (Nowak et al., 2017). Therefore, we employ the definition of speech synchronization in terms of reciprocity and the nonverbal coordination of turn-taking behavior, which creates a conversational rhythm or confluence of performances (Reuzel et al., 2013). We explore speech synchronization, the temporal dimension of leading and follower dynamics, and differences or asymmetries in nonverbal interactional dominance through the turn-taking behaviors exhibited in conversations (Reuzel et al., 2014).

1.1.2. Nonverbal Interactional Dominance in Speech and Personality

Speech synchronization occurs as interacting partners find an optimal, predictable, and cyclic rhythm in the conversation, which allows them to take turns, and exhibit fewer interruptions or prolonged silences (Warner, 1992, Reuzel 2013). These optimal and synchronized rhythms of communication are linked to affiliation (Hove & Risen, 2009), cooperative efficiency (Delaherche et al., 2012), and positive affect (Warner, 1992). Speech is not distributed equally in interpersonal interactions (Bales, 1973), and sometimes one partner influences the interaction and talks more (i.e., interactional dominance), which is associated with prestige and greater influence in decisions in interactions, as well as higher status in other contexts (Meeker, 2020). According to some authors, the speed of speech onset, or given opportunities to speak (response latency), indicates conversation dominance (Berger et al., 1972; Fişek et al., 2005; Meeker, 2020). Other nonverbal indicators of communication imbalances include temporal leader-follower dynamics, regarding having the initiative in the turn-taking structure (Reuzel et al., 2013, 2014). People who more often initiate speech, and lead the dyadic conversation dynamics over time resulting in asymmetries or imbalances in conversation dynamics. On the other hand, possible differences in nonverbal interactional dominance between the interaction partners refer to the extent and average duration of asymmetric episodes in the influence of one conversation partner's nonverbal behavior on the other (Reuzel et al., 2014).

Conversation dynamics, such as speech synchronization, leader-follower dynamics, and nonverbal interactional dominance, allow individuals to fulfill their communicative needs. However, conversation dynamics are also influenced by situational factors and other differences between the interacting partners (Mischel & Shoda, 2005). Thus, we study how variation in Extraversion and Agreeableness are associated with such dynamics.

1.1.3. Personality Conceptualizations and the Emergence of Dyadic Systems

Dynamic personality models suggest that although human affect, behavior, thoughts, desires, and "predispositions" for action change continuously, due to the interplay of intrinsic mechanisms and external forces, they converge into stable personality patterns over time (Bleidorn et al., 2022 for lifespan trajectories, also Nowak et al., 2005; Sosnowska et al., 2019; Revelle & Wilt, 2020). Personality differences have also been operationalized as tendencies or patterns to optimally engage with the world, thus stylistic differences in person-environment fit (Hovhannisyan & Vervaeke, 2022). Personality is then a label for how individuals structure and navigate the flow of (social) affordances across contexts (Gibson, 1979; Chemero, 2003; Satchell et al., 2021). This more contextualized and dynamic view of personality is broader than trait concepts known as characteristic adaptations (Nguyen et al., 2021).

Personality describes how system components differ between conversation partners, and similarity and dissimilarity in personality may promote or hamper the emergence of conversational elements at the higher-order level of the dyadic system that were not present for each individual alone (Mischel & Shoda, 2005; Nowak et al., 2020). We test how the personality characteristics of each interaction partner affect dyadic speech synchronization during different conversation types, and how interacting partners appraise these interactions.

We focus on the personality dimensions of Extraversion and Agreeableness, as they are key to social behavior (Goldberg et al., 1998; McCrae & Costa, 2008; Koole et al., 2001). The three other broad personality dimensions of the Five Factor Model are more relevant to other outcome domains, such as work (Conscientiousness), affective experience and health (Neuroticism), and intellectual/creative life (Openness; see Peabody & Goldberg, 1989; Cuperman & Ickes, 2009; Larsen et al., 2020). Extraversion captures one's sociability and high scores indicate liveliness, gregariousness, cheerfulness, outgoing, and adventure-seeking behaviors, compared to introverted individuals (McCrae & Costa, 2008). Agreeableness reflects the tendency toward altruism, cooperation, and prosocial interactions (Larsen et al., 2020; McCrae & Costa, 2008), while "disagreeable" individuals tend to lack concern for others (De Young, 2015; Hovhannisyan & Vervaeke, 2022).

Previous studies of individual differences in speech patterns demonstrated that the amount of speech of an individual will be affected by factors such as the talkativeness of the interacting partner (Borgatta & Bales, 1953; Leaper & Ayres, 2007; Oben & Brône, 2016), which partly reflects their personality traits (Cuperman & Ickes, 2009). For instance, two extroverts are likely to cover a wide variety of themes and more relatable/ common ground topics in their conversation, while two introverted speakers tend to be more concise and engaged in focused problem themes (Thorne, 1987). Dyads composed of two introverted or two extroverted individuals are likely to take more and longer speaking turns, and to disclose more personal information, versus mixed dyads (introverted/extroverted, see Arellano-Véliz et al., 2024a; Cuperman & Ickes, 2009). Homogeneous introverted or extraverted dyads evaluated their interactions as more positive, natural, and engaging, and felt more accepted and encouraged to lead the conversation and to interact more in the future. In the case of Agreeableness, mixed dyads (agreeable/'disagreeable') tended to self-disclose more personal information, and agreeable individuals tended to evaluate their interaction more positively (vs. disagreeable individuals; also see Arellano-Véliz et al., 2024a). Overall, the question remains whether (higher-order) conversation constraints such as a conversational topic and personality traits can play a significant role in explaining speech synchronization.

1.2. The present study

We propose that speech synchronization dynamics are an emergent factor with a complex nature, and are influenced by personality and contextual differences, among others. To study interpersonal speech dynamics, we analyze conversational behavior (non-verbal) in time series through the dynamics of overall speech synchronization, leader-follower dynamics, and differences or asymmetries in nonverbal interactional dominance. We aimed to elucidate the influence of (high-level) situational constraints (e.g., Paxton & Dale, 2017), which we operationalized as specific conversational topics (i.e., introduction, self-disclosure, argumentative), and individual differences in the personality traits Extraversion and Agreeableness. Furthermore, we scrutinized how these factors shape interaction partners' perceptions and evaluations of the conversation.

1.2.1. Cross-Recurrence Quantification Analysis to Quantify Synchronization of Speech, Leader-Follower Dynamics, and Nonverbal Interactional Dominance

To explore speech synchronization, leader-follower dynamics, and differences or asymmetries in nonverbal interactional dominance we employed three related nonlinear time-series techniques based on Cross-Recurrence Quantification Analysis (CRQA, e.g., Zbilut & Webber, 1992; Marwan et al., 2007; Cox et al., 2016), which are outlined in Table 1 and detail in the Methods section. CRQA offers a powerful means to study the temporal patterns of speech dynamics in interpersonal settings and is especially suitable for studying temporal interdependencies between two time series (e.g., Zbilut et al., 1998; Marwan et al., 2007; Cox et al., 2016). We focus on instances where turn-taking behavior was observed as one person was speaking and the other was silent (similar to Reuzel et al., 2013, 2014).

The nonlinear time-series techniques allowed us to study interpersonal speech dynamics in three different domains. First, we measured speech synchronization (through turn-taking dynamics) globally (at all lags), and simultaneously (at lag-zero), by identifying occurrences where one interacting partner is silent while the other is speaking. Second, we analyzed balance during conversations by quantifying the overall leading-following dynamics (imbalance in having the initiative in turn-taking structures). Third, we explored asymmetries in nonverbal interactional dominance by assessing the influence of one interacting partner over the other (i.e., the influence of one interacting partner on the other). Detailed information about the techniques and variables extracted can be found in the Methods section and Table 1.

Complex dynamic systems techniques can help to study dyadic interaction dynamics and the role of personality traits that surface in reciprocal influences between individuals (e.g., Mischel & Shoda, 2005). Individual differences influence the dyadic system which has emergent properties that would not be present otherwise, for example, a talkative person can generate more opportunities for action in a dyadic interaction. This integration of CRQA with dyadic systems and personality traits provides a comprehensive framework for understanding the multifactorial nature of interpersonal dynamics.

1.2.2. Expectations

This study aimed to answer four research questions with the following hypotheses (See Table 1 for the operationalization of the variables).[1]

1) How are speech synchronization, leader-follower dynamics and differences/asymmetries in nonverbal interactional dominance explained/influenced by (H1a) conversational constraints i.e. different conversational topics? (H1b).

First, we expected that the type of conversation would significantly explain part of the variance of speech synchronization, and that self-disclosing (e.g., Thorson et al., 2021) and argumentative (Tschacher et al., 2018) conversations result in higher synchronization (H1a; see Arellano-Véliz et al., 2024a). In the first case, it could be linked to affiliative drives, whereas in the latter, it could be related to competition (Tschacher et al., 2018) or achievement goals (Allsop et al., 2016). Generally, differences in speech synchronization, leader-follower dynamics, and nonverbal interactional dominance (H1b) were expected, especially in the argumentative task compared to the introduction.

2) To what extent do personality traits and dyad composition explain variation in speech synchronization?

We focused our primary hypotheses on the social traits of Extraversion and Agreeableness based on previous studies (Funder & Sneed, 1993; Cuperman & Ickes, 2009; Arellano-Véliz et al., 2024a).

High Extraversion is characterized in the literature by social enjoyment and talkativeness; while low Extraversion has been linked to (perceived) socially reserved and 'awkward' behavior (Funder & Sneed, 1993; Cuperman & Ickes, 2009). Therefore, higher scores on Extraversion were expected to increase dyadic speech synchronization while introverted dyads were expected to synchronize less (H2a). When at least one of the dyadic partners is extroverted we expect more speech synchronization (H2b; Arellano-Véliz et al., 2024a).

Additionally, we expected that high scores on Agreeableness would be associated with stronger dyadic coupling thus increased speech synchronization (H2c, vs. disagreeable dyads).[2] The link between Agreeableness and dyadic synchronization roots in the reported warmth, 'cheerful', and friendly behavior linked to this trait (Funder & Sneed, 1993; Cuperman & Ickes, 2009), which would contribute to better dyadic coupling (e.g., Arellano-Véliz et al., 2024a). Low Agreeableness was expected to hamper dyadic synchronization in dyads with at least one low-agreeable individual (H2d). An exception

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1 Since this study is part of a larger data collection and a subsample was considered, we delineate our hypotheses based on Arellano-Véliz et al. (2024a) which focused on synchronization and coupling of body motion, as well as pioneer literature by Funder & Sneed (1993), Cuperman & Ickes (2009) and Tschacher et al. (2018).

2 We based this hypothesis in the results found in (Arellano-Véliz et al., 2024a) evidencing increased Entropy (interpreted as coupling) between agreeable individuals.

to this would be the argumentative conversation, where competing goals can increase the synchronization of speech in low-agreeable individuals (H2e).

3) To what extent do personality traits and dyad composition explain variation in distinct patterns of leader-follower dynamics and differences/asymmetries in nonverbal interactional dominance?

Higher scores of Extraversion would be associated with a more imbalanced distribution of speech when interacting with introverts, where they could take a leading behavior and exhibit asymmetries in nonverbal intersectional dominance (H3a). Higher scores on Agreeableness are expected to explain balanced and symmetric dynamics of speech in the conversations, conversely to individuals with low scores on Agreeableness (H3b).

4) How do speech synchronization, leader-follower dynamics, and nonverbal interactional dominance impact the perceived quality of interactions among participants?

We expected that higher levels of synchronization of speech (H4a), balanced (leader-follower), and symmetric (lower differences in nonverbal interactional dominance) interactions (H4b) would be positively linked to perceived interaction quality, indicating that individuals who exhibit more aligned speech patterns will perceive the interaction more positively. In addition, based on previous studies, it is expected that higher scores on Extraversion (H4c) and Agreeableness (H4d) will explain positive perceptions of the interaction, especially linked to synchronized interactions.

2. Method

2.1. Participants

Data presented in this paper were collected between 2021 and 2022 in the context of a larger multimodal experimental project (see Arellano-Véliz et al., 2024a). From 300 screened participants, 112 undergraduate students participated in a 15-minute conversation in same-sex dyads in a laboratory room. A subsample of 100 participants (50 same-sex dyads) aged 18-33 (mean = 20.54, SD = 2.74; 72 females, 28 males) constituted the final sample, as these data were suitable for study analyses (i.e., audio files integrity was adequate to be analyzed, which was not the case in six dyads). They received ECTS credits for participating in the study and provided informed consent according to the ethical requirements to conduct research with human participants (ethical approval code PSY-1920-S-0525).

In principle, we designed the laboratory study by focusing on the (dis)similarity in socially relevant traits scores, particularly, Extraversion and Agreeableness, either 0.5 SD above ("high") or 0.5 SD below ("low") the sample mean (e.g., Li et al., 2020). In our models, we used the full sample of 100 participants as we modeled the personality traits of interest continuously while preserving the dyadic structure in a parsimonious way. In addition, we provide plots and descriptives following this thresholding dyadic matching (similar to the threshold described by Li et al., 2020 for low/high scores and the approach of Cuperman & Ickes, 2009).

2.2. Instruments

2.2.1. Big Five Personality Traits: International Personality Inventory Pool—120 (IPIP-NEO-120)

Personality traits were assessed utilizing the IPIP-NEO-120 (Johnson, 2014) through the Qualtrics online platform before the laboratory study was conducted, approximately 10 days before the laboratory study took place, and participants provided informed consent for this screening part of the study. The IPIP-NEO-120 is a self-report questionnaire comprising 120 items that measure the Big Five personality traits Extraversion, Neuroticism, Openness to Experience, Agreeableness, and Conscientiousness, and their 30 facets (5*6). The completion of the questionnaire takes between 10 and 20 minutes on average according to the author (Johnson, 2014). The psychometric properties (Johnson, 2014) are consistent with the psychometric properties of the NEO-PI-R scales (McCrae & Costa, 2008), which indicates that the IPIP-NEO-120 is reliable and valid. Furthermore, in a sample of 501 individuals, the scales of the IPIP-NEO-120 and NEO-PI-R exhibited high correlations (Extraversion 0.85, Neuroticism 0.87, Openness to Experience 0.84; Agreeableness 0.76 and Conscientiousness 0.80 (all $p <.01$), Johnson, 2014). The IPIP-NEO-120 exhibited good internal consistency (Cronbach's alpha of 0.84, 0.88, 0.85, 0.81, and 0.84, respectively). The IPIP-NEO-120 is publicly available and has cross-cultural robustness, thus, suitable for an international sample.

2.2.2. Self-disclosure paradigm

We employed the self-disclosure paradigm to create an affiliative conversation (Aron et al., 1997). This paradigm consists of an experimental protocol in which both interacting partners ask and answer a set of questions, which become increasingly more personal. The protocol aims to create interpersonal closeness in an experimental context. The original version has three sections with 12 questions each, taking approximately 45 minutes to complete. We shortened the protocol to three sets of questions each (9 questions in total) since this part of the conversation lasted 5 minutes in our study. They were asked to choose at least one question from each set (e.g., "What would constitute a 'perfect' day for you?"; "Is there something that you've dreamed of doing for a long time? Why haven't you done it?"; "How do you feel about the relationship with your family?").

2.2.3. Perception of the Interaction (appraisals)

After the dyadic conversation, participants were asked to complete a modified version of the Perception of the Interaction questionnaire (Cuperman & Ickes, 2009) to assess the self-reported interaction experience. The scores go from 1 ("not at all") to 5 ("very much"). The original version of this questionnaire assesses the first-person perspective (e.g., "To what extent did you feel accepted and respected by the other person"?) and the third-person perspective (e.g., "To what extent do you think your conversation partner felt accepted and respected by you?). In the present study, we report the first-person questions, as our research focused on individual experience, instead of actor-partner interdependence effects. To preserve nuanced interpretations the Perception of Interaction questionnaire items were used as variables, each provided in Table 2, instead of clusters of items, following the precedent by Funder and Sneed (1993) and Cuperman & Ickes (2009).

2.3. Procedure

Participants were invited to participate in the experimental study, and provided with a heart rate transmitter belt when they arrived in the laboratory, although these data are not part of this paper. After their arrival, participants were asked to read and sign the informed consent, and then fill in an affect score. Subsequently, a microphone was attached to their clothing, and instructions about the conversation task were given. Participants engaged in their interpersonal tasks standing face-to-face on a balance board (designed for measuring postural control, also not reported in this paper), at a fixed distance of 1.5 meters. A camera positioned approximately 4.5 meters away recorded the interaction from a sagittal perspective.

The conversation followed an approximately 15-minute semi-structured interaction schedule with three parts of approximately 5 minutes each, although participants had the freedom to finish each part before moving to the next one. In each conversation, participants (1) introduced themselves, (2) self-disclosed, and (3) engaged in an argument or debate. In the introduction phase, participants were instructed to briefly introduce themselves to their interacting partner within 5 minutes. Some general themes were provided as examples in case guidance was needed. The subsequent "self-disclosure" phase involved participants asking each other questions using a modified version of Aron et al.'s (1997) self-disclosure paradigm. Participants selected questions to discuss for 5 minutes, and both individuals were required to answer each question. They were given the freedom to decide what they wanted to share with their partner. In the argumentative phase, participants selected a conversational topic from a pool of around 20 and took opposing sides (pro/against) on topics such as "Are strict lockdowns a valid measure during the pandemic to keep people safe?"; "Are dating apps a good platform for meeting a romantic partner?"; "Should pre-adolescents and adolescents use social media freely?" For these example items, participants had to choose a position, such that the dyads had conflicting arguments, and they discussed as many topics within 5 minutes, with the time controlled by an alarm. However, participants were instructed to conclude their conversation before moving on to the next phase, therefore, each part could last for longer than 5 minutes if necessary. Following the interaction, each participant completed questionnaires on affective state, interpersonal closeness, and interaction appraisals.

2.4. Data Processing and time series generation

Data streams were recorded using the Lab Streaming Layer software (Kothe et al., 2019) and each audio stream was cleaned using Adobe Audition to remove the background noise by employing the default 'noise print' and 'DeNoise' functions on each audio file until the background noise and the voice of the interacting partner in the background were mostly canceled. With the resulting cleaned files we used the voice activity annotation function on the Praat software (Boersma et al., 2023) to code silence and speech segments, being categorized as '0 = silence' and '1 = speech' similar to the procedure described by Reuzel et al (2014). This procedure resulted in a dichotomous time series consisting of 1's and 0's for each interacting partner (see Figure 1). Since the software is sensitive to the phonetic level (phoneme and syllable boundaries), we resampled the time series closer to the utterance level, defining 1 second per silence and speech segments (e.g., see Situation Model by Pickering & Garrod, 2004; Abney et al., 2014).

Figure 1. Representation of the time series generation

Time (seconds)	1 2 3 4 5 6 7 8 9 10…
Time series participant "A"	0 0 0 1 1 1 1 1 1 0 …
Time series participant "B"	0 0 1 1 1 0 0 0 0 1 …

Note: The figure represents the coding of the time series, which represents the speech (1) and silence (0) segments by seconds in the time series of each interacting partner (Figure adapted from Reuzel et al., 2013).

2.5. Time series technique and statistical analyses

2.5.1. Categorical Cross-Recurrence Quantification Analysis (CRQA)

Cross-Recurrence Quantification Analysis (CRQA) was used to quantify the degree of speech synchronization or dyadic coupling. CRQA is a nonlinear bivariate correlation technique based on recurrence analysis to quantify the temporal similarity or coupling properties between time series (Zbilut et al., 1998; Marwan et al., 2007; Wallot & Leonardi, 2018). CRQA is the extended bivariate form of the original Recurrence Quantification Analysis (RQA), and it is used to study the coupling of two time series, in the case of our study, both conversational partners (Marwan et al., 2007). The main tool, the cross-recurrence plot is built by identifying and noting down in a 2D plot all instances where the behavior of the two-time series match (e.g. Cox et al., 2016; Xu et al., 2020; Wallot & Leonardi, 2018; see Figure 2), and these recurrence measures describe the temporal dynamics of the interacting systems across all possible lags or time scales (Zbilut et al., 1998; Marwan et al., 2007).

We employed a categorical form of CRQA given the categorical (dichotomous) nature of our data, computed with one time series for each interaction partner with codes “1” and “0” for speech and silence occurrences respectively (see Figure 1). In this case, a match (i.e. recurrence) is noted down as a dot in the cross-recurrence plot, when one interaction partner is silent and the other one speaks (which are “1” and “0” or “0” and “1” combinations in the respective time series). Consequently, a line in the cross-recurrence plot (i.e. sequence of matching points), corresponds to the prolonged co-occurrence of speech and silence. CRQA enables us to quantify the synchronization or behavioral attunement between interacting partners during the conversation, from the temporal patterns present in the time series (Reuzel et al., 2013). CRQA identifies recurrences in the behavior between dyadic partners throughout the conversation, which can be simultaneous or in temporal proximity (with some delay) (Cox et al., 2016).

We conducted two follow-up analyses: Diagonal Cross-Recurrence Profile (DCRP) and anisotropic CRQA (aCRQA). With DCRP we analyzed the leader-follower dynamics in the conversation. That is, it quantified the imbalance between the interaction partners with respect to having the initiative in the turn-taking structure. aCRQA enabled us to investigate possible differences in nonverbal interactional dominance between the interaction partners. That is, it quantified the extent and average duration of asymmetric episodes in the influence of one conversation partner’s nonverbal behavior on the other. Each of these analyses will be explained in more detail below. All variables in this study are defined in Table 1, such as RR_{global}, which quantifies the recurrence rate across the entire cross-recurrence plot.

2.5.2. Diagonal Cross-Recurrence Profile (DCRP)

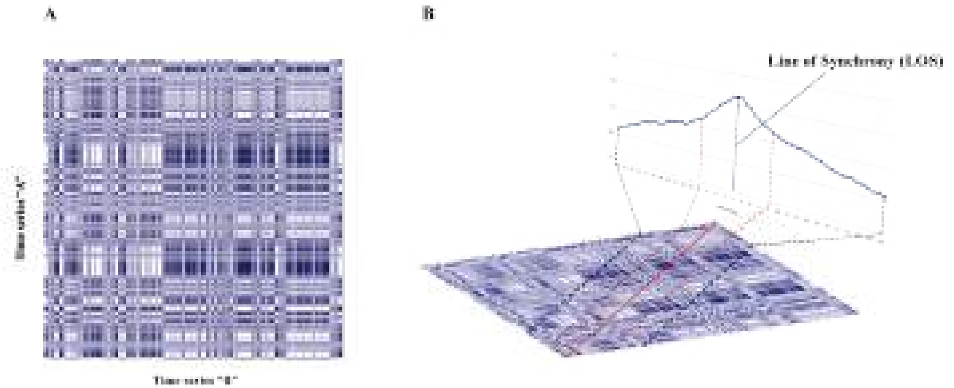
We examined balance/imbalance in leading-follower dynamics during the dyadic conversations with Diagonal Cross-Recurrence Profile analyses (DCRP, Richardson & Dale, 2005). DCRP quantifies the number of recurrences at different lags across the main diagonal or line of synchrony of the cross-recurrence plot, see Figure 2B (Wallot & Leonardi, 2018; Tomashin et al., 2022). The main diagonal of the cross-recurrence plot is called the Line of Synchrony (LOS) and captures simultaneous matching behaviors at lag-zero. That is, occurrences when one participant speaks (code "1") while the other is silent (code "0"), at the same time. The diagonals parallel to the LOS display instances where these recurrences (matching behaviors) occur with some delay, which increases the further one moves away from the LOS. The distribution of recurrences at one side of the LOS indicates how much (and how quickly) the behaviors of one participant in the time series are followed by the matching behaviors in the other participant, for different lags. Importantly, it is likely that the recurrences on both sides of the LOS are asymmetrically distributed (Wallot & Leonardi, 2018), creating a diagonal cross-recurrence profile (DCRP). The DCRP quantifies leader-follower imbalances in the conversation (Dale et al., 2011; López Pérez et al., 2017). We computed the absolute Quotient of the DCRP (Q_{DCRP}) to indicate the overall conversational imbalance in leading and following between the interaction partners (see Table 1; Richardson & Dale, 2005; Dale et al., 2011).

2.5.3. Anisotropic CRQA (aCRQA)

To further examine asymmetries in nonverbal interactional dominance in conversations we used Anisotropic CRQA (aCRQA; Cox et al., 2016; Xu et al., 2020). Categorical time series tend to form horizontally or vertically oriented rectangular structures in cross-recurrence plots which indicate coupling between two time series (see Figure 2A). aCRQA quantifies the relative influence of each interacting partner on the other by capturing matched behaviors over time and separately quantifying the distribution of vertical and horizontal structures in the cross-recurrence plot (Cox et al., 2016; Xu et al., 2020). These structures represent behaviors performed by each partner, matched for extended periods by the other. Thus, one partner effectively captures the behavior of the other during certain episodes. The difference between horizontal and vertical structures indicates whether one interaction partner captures the other partner to a larger degree. aCRQA analyzes horizontal lines and vertical lines separately and quantifies their (relative) differences, in amount, and length, among others. Differences in these measures indicate an asymmetry in dominance, that is, unequal coupling strength between the interacting partners (Cox et al., 2016; López Pérez et al., 2017).

Differences in Laminarity (LAM_{ARD}) and Trapping Time (TT_{ARD}) quantify overall asymmetries in the conversation (see Table 1). It is important to note that asymmetries in nonverbal interactional dominance indicate that one of the interaction partners tends to exhibit more control, capturing the other partner into matching behaviors for extended periods (van Dijk et al., 2018). This is not necessarily a negative aspect of the interaction, as the term 'dominance' might suggest. Dominance merely describes potential asymmetries in the coupling strength of the dyadic system during the conversations. We focus on turn-taking dynamics (speech and silence episodes) during the conversation, expressed by horizontal and vertical rectangular structures in the plot, which capture the behaviors displayed by each interaction partner respectively. These behaviors can also represent the creation of opportunities (or affordances) for episodes of speech and silence in the conversation. Therefore, nonverbal interactional dominance can have a positive social communicative effect in such cases.

Figure 2. Cross-Recurrence Plot and Diagonal Cross-Recurrence Profile



Note: Panel 2A. The figure represents a categorical cross-recurrence plot. In this case, the matching between the two interacting partners (time series) was defined as one person speaking (categorized as 1) and the other person being silent (categorized as 0). In the plot, these occurrences are represented by the blue lines or blocks, whereas the non-occurrences –both speaking (1-1) or both in silence (0-0)– are represented by white spaces. Panel 2B. Diagonal Cross-Recurrence Plot (DCRP) representation. Adapted from Wallot & Leonardi (2018). The profile can help determine the coupling direction of time series in terms of leading and following dynamics at different lags along the line of synchrony (LOS). Each line parallel to the line of synchrony represents a particular delay or lag in the alignment of speech dynamics between both interacting partners. A lag of 0 indicates synchrony or simultaneous recurrence. In the context of turn-taking, this represents moments when both individuals are engaged in speaking or listening at the same time, suggesting coupling, reciprocity, and attunement.

Table 1. Cross-Recurrence Quantification Analysis: Measures, Description, and Interpretations

Measure	Formula and Description	Interpretation
Overall Speech Synchronization (coupling) - CRQA		
Recurrence Rate RR_{global}	Sum of recurrent points in cross-recurrence plot divided by the size of cross-recurrence plot. Measures the overall rate (proportion) of recurrent points (matches) between the two time series across the entire cross-recurrence plot. Matching was specified as one person speaking while the other was silent (1-0, 0-1 occurrences).[1]	RR_{global} estimates synchronization across all possible lags (delays). Higher RR_{global} indicates more speech synchronization across all possible lags (greater engagement in turn-taking episodes), and more structured and responsive interactions. A low(er) RR_{global} indicates less synchronization, more interruptions, silences, and a more irregular pattern of coupling.[1]
Recurrence Rate through the Line of Synchrony RR_{LOS}	Sum of RR points on the line of synchrony divided by the length of the line of synchrony (= length of time series). The rate (proportion) of recurrence (matching) on the line of synchrony represents the instances where speech and silence co-occur (simultaneously). It represents the percentage of synchrony.[1,2,3]	RR_{LOS} is a measure of synchrony or coupling in speech at lag-zero (simultaneous). Higher RR_{LOS} suggests more co-occurrence of speech and silence thus synchronization at the same time and, therefore, responsive interactions. Conversely, a lower RR_{LOS} indicates less synchronization, more interruptions, and silences at lag-zero (simultaneously).[1]
Leading-Following Dynamics (DCRP)		
Quotient of Diagonal Cross Recurrence Profile, Q_{DCRP} (absolute)	$\lvert(RR_{right} - RR_{left} / \; RR_{right} + RR_{left})\rvert$ RR_{right} and RR_{left} refer to the recurrence rates on the left and right sides of the LOS, respectively, within the DCRP (see Figures 2B and 6).[1, 2, 3]	Q_{DCRP} indicates the absolute overall degree of balance/imbalance between the left and right sides along the LOS.[4] Leading-follower dynamics can be inferred from this measure, where 0 represents a totally balanced interaction (i.e. equally leading and following), and 1 represents the situation where one of the interacting partners is leading during the entire interaction.[1]

Table 1. Cross-Recurrence Quantification Analysis: Measures, Description, and Interpretations (continued)

Measure	Formula and Description	Interpretation
Asymmetries in Nonverbal Interactional Dominance (aCRQA)		
Relative Difference in Laminarity of Anisotropic CRQA, LAM_{ARD}	$\lvert (LAM_{ver} - LAM_{hor}) \rvert / (LAM_{ver} + LAM_{hor}) \rvert$ $LAM_{ver,}$ and LAM_{hor} refer to the Laminarity of vertical (interacting partner "A") and horizontal lines (interacting partner "B"), respectively. Laminarity is a recurrence measure that quantifies the presence of vertical and horizontal lines in the DCRP, indicating periods of repeated fixed behavioral patterns in the dynamics of the conversation. The relative difference in Laminarity compares the Laminarity along specific directions (i.e. horizontal and vertical), reflecting variations in the leading-following (balance) dynamics between conversational partners.[4]	Asymmetric laminar patterns indicate conversation dominance. A higher relative difference in Laminarity suggests the overall asymmetry's magnitude in the interactions' nonverbal interactional dominance. If one dyadic partner more often initiates the talking and silences this steers episodes of silence or speech in the other. Hence, one person "affords" or gives the other opportunities to display behavior to the partner, and thus is more "dominant" or influential in the conversation.[4] Low LAM_{ARD} implies a more "balanced" interaction when nobody consistently takes the lead over the other.
Relative Difference in Trapping Time of Anisotropic CRQA, TT_{ARD}	$\lvert (TT_{ver} - TT_{hor}) \rvert / (TT_{ver} + TT_{hor}) \rvert$ TT_{ver} and TT_{hor} refer to the Trapping Time of vertical (interacting partner "A") and horizontal lines (interacting partner "B") respectively. Trapping Time quantifies the average duration for which one system "traps" or captures the behavior of the other system. It quantifies the average temporal persistence of one system's influence on the other.[4]	One partner's speech and silence episodes lead ("trap") the other partner in relatively longer or shorter episodes of silence and speech, respectively. A longer trapping time indicates a sustained influence of one speaker on the other or nonverbal interactional dominance. A shorter trapping time suggests swift reciprocal interactions, where both speakers influence one another. It can be indicative of a higher interactional sensitivity or responsivity.[4]

Note. RR= Recurrence Rate, CRQA= Cross-recurrence quantification analysis. aCRQA= Anisotropic Cross-recurrence quantification analysis. DCRP= Diagonal Cross Recurrence Profile. LAM= Laminarity. LOS= Line of Synchrony. TT= Trapping Time. References: 1 Reuzel et al. (2014); 2 Richardson & Dale (2005), 3 Wallot & Leonardi (2018), 4 Cox et al. (2016). CRQA analyses were performed using Marwan's CRP toolbox (2024, available at https://tocsy.pik-potsdam.de/CRPtoolbox) on MATLAB (2022).

2.5.4. Models

First, we performed maximum likelihood mixed-effects models with two levels to test our research questions regarding interpersonal synchronization of speech, task effects, and personality traits. Level 1 was the task or type of conversation (3 observations), nested within the dyadic structure (Level 2). We employed the "lme4" R package, and the degrees of freedom and significance were calculated using the Satterthwaite method, which is suitable for small sample sizes and complex model structures (Bates et al., 2015). First, we performed models predicting the effect of the task on each speech synchronization and nonverbal interactional dominance variable. The predictor variable was the task (conversational topic), a categorical variable with three levels (introduction/self-disclosure/argumentative), where the introduction was the baseline and the response variables were RR_{global}, RR_{LOS}, Q_{DCRP}, LAM_{ARD}, and TT_{ARD}, respectively. Next, we modeled the effects of the personality traits Extraversion and Agreeableness and tasks on speech synchronization, leader-follower dynamics, and nonverbal interactional dominance. The response variables were RR_{global}, RR_{LOS}, Q_{DCRP}, LAM_{ARD}, and TT_{ARD}, the predictors were the personality traits of each interacting partner and task.[1] We report both estimates and standardized beta weights (β) which can be interpreted as effect sizes (e.g., Paxton & Dale, 2013). For linear mixed effects, all continuous predictors were standardized before being incorporated into the models to obtain beta weights. Particularly, personality variables were centered by subtracting the mean and scaled by the standard deviation (R core team, 2022).

Subsequently, to explore the effects of speech synchronization and nonverbal interactional dominance on the perceptions of the interactions (appraisals assessment), generalized linear models were conducted. We selected as predictors one variable of speech synchronization (RR_{LOS}) as this is the basic measure that provides information on speech synchronization simultaneously (lag-zero); a variable informing about leader-follower dynamics from the DCRP analysis (Q_{DCRP}), and one about nonverbal interactional dominance extracted from aCRQA (LAM_{ARD}), which provides information about the extent of asymmetries in nonverbal interactional dominance. We included the items of the perception of interaction questionnaire as the response variable (see Table 2), while the speech synchronization/interactional dominance variables and personality traits were the predictors.[2] The Benjamini-Hochberg (BH, 1995) method was employed to correct the p-values allowing for a flexible balance between detecting true effects and limiting false positives compared to more conservative methods like Bonferroni.

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*1 The models followed the structure: [RRLOS ~ (Extraversion A * Extraversion B) * Task + (1|Dyad)]. In this example, Extraversion A and B correspond to the scores of each interacting partner. The same procedure was employed for the other response variables and Agreeableness*

*2 The models followed the structure (example): Perception of Interaction Variable 1 ~ RRLOS * (Extraversion A * Extraversion B).*

Table 2. First-Person Perception of the Interaction Variables (Cuperman & Ickes, 2009)

Variable
1. How much did you feel a need to communicate with the other person?
2. How much did you use the other person's behavior as a guide for your own behavior?
3. To what degree did you attempt to take the lead in the conversation?
4. How self-conscious did you feel when you were with the other person?
5. To what degree did the interaction seem awkward, forced, and strained to you?
6. To what degree did the interaction seem smooth, natural, and relaxed to you?
7. How involving (engaging) did you find the interaction?
8. To what extent did you feel put down, patronized, or rejected by the other person?
9. To what extent did you feel accepted and respected by the other person?
10. To what extent would you like to interact more with the other person in the future?
11. How much did you enjoy your interaction with the other person?
12. To what extent did you try to accommodate to the other person by adapting your behavior to "fit in" with his/hers?
13. How comfortable did you feel around the other person?
14. How much did you like the other person?
15. How empathic and understanding was the other person?

Note: Items were Likert-style from 1 to 5 (1=not at all, 2= a little bit, 3=moderately, 4=very much, 5=extremely).

3. Results

Descriptive statistics for all variables are provided in Table 3. Average speech time in seconds was the longest when participants introduced themselves (mean = 467.14 seconds, SD = 78.53), followed by self-disclosure (mean = 456.4, SD = 84.04), and shortest during the argumentative conversation (mean = 445.92 seconds, SD = 86.94).

Using mixed-effects models we assessed whether dyadic speech synchronization, leader-follower dynamics, and nonverbal interactional dominance differed across the three conversation phases: Introduction, Self-Disclosure, and Argumentation. The Introduction task served as the baseline and we examined response variables including the Recurrence Rate Global (RR_{global}), Percentage of Speech across the Line of Synchrony (lag-zero) (RR_{LOS}), Quotient Diagonal Cross-Recurrence Profile (absolute) (Q_{DCRP}), Relative difference of anisotropic Laminarity (LAM_{ARD}), and Relative difference of anisotropic Trapping Time (TT_{ARD}; descriptives are provided in Table 3). Cross-recurrence plots of dyads during the three tasks are illustrated with one example in Figure 3. Mixed effect model estimates are provided in Figure 4 and Table 4.

Table 3. Descriptive statistics

	1. Introduction				2. Self-disclosure				3. Argumentative			
Variable	**M**	**SD**	**Mdn**	**Range**	**M**	**SD**	**Mdn**	**Range**	**M**	**SD**	**Mdn**	**Range**
Speech time (sec.)	467.14	78.53	461	306, 616	456.4	84.04	469	258, 617	445.92	86.94	443.5	230, 671
RR_{global}	0.46	0.06	0.47	0.26, 0.54	0.46	0.05	0.47	0.32, 0.55	0.47	0.06	0.49	0.30, 0.58
RR_{LOS}	0.56	0.14	0.59	0.17, 0.85	0.55	0.14	0.56	0.13, 0.80	0.58	0.15	0.58	0.10, 0.82
Q_{DCRP}	0.02	0.02	0.02	0, 0.05	0.03	0.02	0.02	0, 0.12	0.03	0.03	0.03	0, 0.10
LAM_A	0.93	0.03	0.94	0.82, 0.98	0.94	0.04	0.95	0.81, 0.99	0.94	0.04	0.95	0.75, 0.99
TT_A	8.17	2.63	7.92	4.24, 18.8	8.74	4.46	8.07	3.7, 46.29	9.51	3.77	8.7	4.55, 25.95
LAM_{ARD}	0.02	0.02	0.02	0, 0.11	0.02	0.02	0.02	0, 0.07	0.02	0.02	0.02	0, 0.07
TT_{ARD}	0.15	0.13	0.09	0.01, 0.54	0.16	0.13	0.12	0.11, 0.53	0.16	0.10	0.13	0.01, 0.44

N = 100 participants (50 dyads). M = mean, SD = standard deviation, Mdn = median. RR_{global}= Recurrence Rate Global, RR_{LOS}= Percentage of Speech across the line of Synchrony (lag-zero), Q_{DCRP} = Quotient Diagonal Cross-Recurrence Profile (absolute), LAM_A= anisotropic Laminarity, TT_A= anisotropic Trapping Time, LAM_{ARD}= Relative difference of anisotropic Laminarity, TT_{ARD}= Relative difference of anisotropic Trapping Time. Anisotropic Laminarity (LAM_A) and anisotropic Trapping Time (TT_A) are the measures from where the relative difference of anisotropic Laminarity (LAM_{ARD}) and Trapping Time (TT_{ARD}) were calculated respectively.

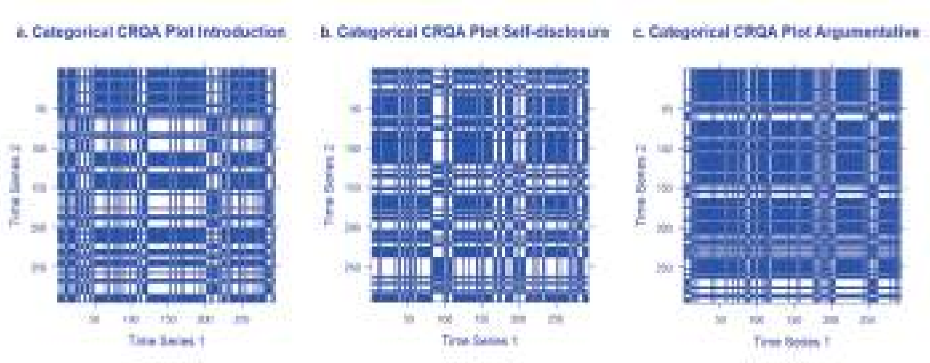
3.1. Interpersonal speech dynamics of speech by conversation topic

Our global measure of speech synchronization (RR_{global}) differed between conversational topics (see Figure 4A), being lowest during the introduction and highest during the argumentative conversation (argumentative > introduction, $t_{(100)}= 2.86$, $p< .01$), which aligns with H1a, and indicates higher synchronization of turn-taking behaviors across all lags. Similarly, imbalances in leading-follower dynamics (Q_{DCRP}) were higher during the argumentative conversation than during introductions (argumentative > introduction, $t_{(100)}= 2.92$, $p< .01$), in line with H1b (Figure 4C). Hence, we observed imbalances between the interaction partners' initiative in the turn-taking structure: one of the participants initiated or led more during dyadic conversations than the other who followed more (see Table 4).

During self-disclosure conversations the dyads showed greater asymmetries in the average duration of nonverbal interactional dominance episodes (or "trapping" episodes) than during introductions (TT_{ARD} self-disclosure > introduction, $t_{(100)}= 2.43$, $p <.05$). Similarly, during the self-disclosure and argumentative conversations dyads showed longer "trapping" episodes (higher TTARD, $t_{(100)}= 2.14$, $p <.05$), in line with H2c (see Figure 4E). Specific task effects were not significant for RR_{LOS} and LAM_{ARD}, suggesting that speech synchronization at lag-zero and the overall asymmetries of nonverbal interactional dominance did not significantly differ across tasks in our sample (see Figures 4B and 4D respectively).

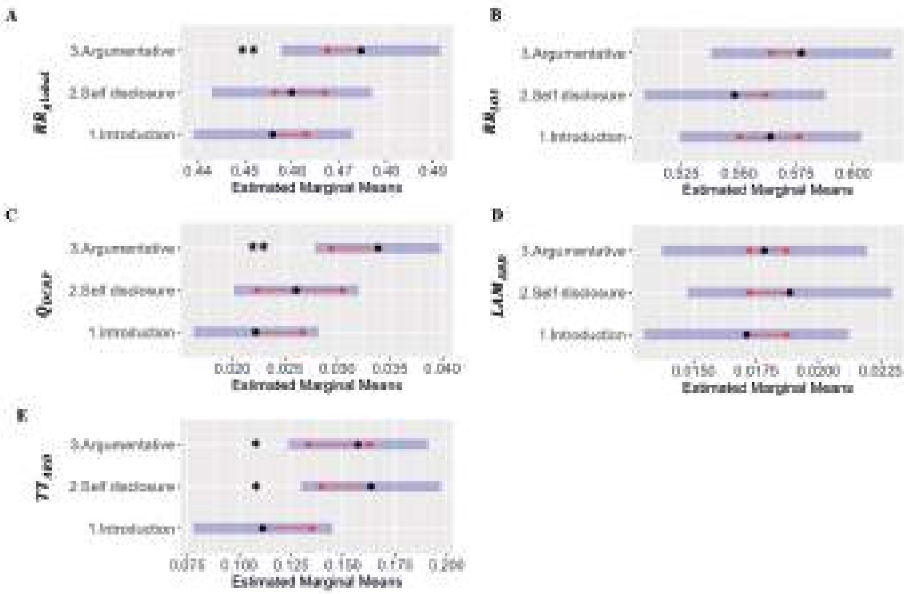
Our results suggest that different conversation types like introduction, self-disclosure, and arguments can have distinct effects on speech synchronization (through turn-taking behaviors), leader-follower dynamics, and the duration of nonverbal interactional dominance. Argumentative conversations were characterized by more speech synchronization and greater imbalances in leader-follower dynamics. During self-disclosure and argumentative conversations, asymmetries sin nonverbal interactional dominance lasted longer than during introductory conversations.

Figure 3. Cross-recurrence plots



Note: Cross-recurrence plots depict interaction dynamics in three tasks: A. Introduction, B. Self-disclosure, C. Argument. The horizontal and vertical axes, "Time Series 1" and "Time Series 2" respectively, represent the time series of both interacting partners. Vertical lines represent temporal influence from one partner to the other, while horizontal lines signify reciprocal influence. Dark lines indicate matching behavior (speaking/silent); and white spaces indicate non-matching behaviors (e.g., simultaneous talking or silence). In the introduction (A), scattered patterns suggest exploratory interaction, with instances of one participant leading. Self-disclosure (B) shows pronounced matching blocks, indicating one participant's stronger influence. In the argumentative task (C), behaviors are evenly distributed, reflecting mutual temporal influence and response between participants.

Figure 4. Estimated Marginal Means of topic predicting each CRQA, DCRP, and aCRQA measure



*Note: * p<.05, ** p<.01. The plots represent the estimated marginal means for each measure of speech dynamic organization. The central points or markers represent the adjusted means of the response variable for different levels of the predictor variables, accounting for the effects of other variables in the model. The blue bars are confidence intervals for the Estimated Marginal Means, and the red arrows indicate comparisons between the means of the tasks with the baseline task (Introduction). CRQA= Cross-Recurrence Quantification Analysis, DCRP= Diagonal Cross Recurrence Profile. aCRQA= anisotropic Cross-Recurrence Quantification Analysis. RR_{global}= Global recurrence rate (speech synchronization at all-lags). RR_{LOS}= Recurrence rate across the line of synchrony (lag-zero). Q_{DCRP}= Quotient of Diagonal Cross Recurrence Profile (balance in leader-follower dynamics). LAM_{ARD}= Laminarity absolute relative difference (asymmetries in nonverbal interactional dominance). TT_{ARD}= Trapping Time absolute relative difference (duration of episodes of nonverbal interactional dominance). Conversation topic 1 (Introduction) was the baseline.*

3.2. Speech Synchronization and Personality

To estimate how personality differences predicted speech dynamics we fit mixed effects models that revealed how more Extraversion predicted global speech synchronization (RR_{global}) across conversational topics. At least one extravert in a dyad predicted lower global speech synchronization during the argumentative conversation than during the introduction (β= -.22, $t_{(100)}$= -2.04, p <.05; see Table 5, Model 1). Extraverts often had higher speech synchronization levels (RR_{global}, see Table 5), which would be indicative of attunement in conversations and turn-taking dynamics across all lags, and all conversational topics (aligned to H2a). Introverted participants showed the most pronounced differences between conversational topics, as they had the lowest global speech synchronization (RR_{global}) during the introduction, and the highest synchronization during the arguments, see Figure 5A. Dyads with extraverted participants synchronized smoothly in all conversation topics (high RR_{global}).

When we focus on Agreeableness we see that high scores of at least one partner predicted reduced global speech synchronization during the argumentative conversation compared to the introduction (RR_{global}, see Table 6, Model 1; β= -0.26, $t_{(100)}$= -2.37, p <.05). Hence, higher Agreeableness predicted decreased global speech synchronization (i.e. RR_{global} values), which argued against H2c, but it may also indicate more silences or simultaneous talking (overlap). Low Agreeableness, in contrast, predicted the highest dyadic global speech synchronization during argumentative conversations (see Figure 5B), which supported H2e. Synchronization of speech through the line of synchrony –at lag-zero or simultaneous (RR_{LOS}), indicated that only Agreeableness predicted differences during the argumentative task compared to the introduction (β= -0.18, $t_{(100)}$=-2.01, p <.05). Here, lower Agreeableness scores predicted strong synchronization (RR_{LOS}, see Table 6, Model 2), in support of H2e, which suggests increased turn-taking dynamics, attuned and swift conversational exchanges without delay (at lag-zero).

In summary, Extraversion significantly predicted differences in global speech synchronization across conversational topics. Extroverted individuals often showed more speech synchronization, suggesting greater engagement in turn-taking dynamics across various conversation topics. The differences in global speech synchronization between conversation topics are most pronounced in low extroverted individuals, with synchronization being lowest during introductions and highest during argumentative conversations. Agreeableness also influenced global speech synchronization, particularly during argumentative conversations compared to introductions. Higher Agreeableness scores predict lower global speech synchronization values, suggesting more silences or overlapping speech, while lower scores predict higher synchronization during argumentative conversations. Lower Agreeableness scores predict higher scores on the line of synchrony, indicating increased turn-taking dynamics and more attuned conversational exchanges without delay. Overall, Extraversion and Agreeableness had varying effects on speech synchronization across different conversational topics. While high Extraversion consistently predicted higher levels of speech synchronization across topics, high Agreeableness showed nuanced effects, with its influence depending on the specific conversational context.

3.3. Leader-Follower Dynamics and Nonverbal Interactional Dominance

When exploring the balance of leader-follower dynamics the models based on the Quotient of Diagonal Cross Recurrence Profiles (Q_{DCRP}) exhibited a significant additive effect during the argumentative task in the models of Extraversion (β = 0.54, $t_{(100)}$ = 3.02, $p < .01$, see Table 5, Model 3) and Agreeableness (β = 0.50, $t_{(100)}$ = 2.81, $p < .01$, see Table 6, Model 3). During the argumentative conversation, the leader-follower imbalances strengthened (more Q_{DCRP}), thus one of the interacting partners typically took the initiative, e.g., spoke first while the dyadic partner followed those rhythms. There were no significant effects of Extraversion linked to leader-follower dynamics (H3a not supported). Higher Agreeableness scores predicted more balanced interactions (lower Q_{DCRP}) during the self-disclosure task than when introducing oneself (β = 0.56, $t_{(100)}$ = 3.06, $p < .01$). Higher scores on Agreeableness predicted larger leader-follower imbalances (high Q_{DCRP}) when self-disclosing, and more balanced conversations during the introduction (see Figure 5D). This indicates that low Agreeableness was associated with higher imbalances in leading-following dynamics, while higher scores on Agreeableness were associated with more balance when introducing themselves (supporting H3b). However, during the self-disclosure task, higher Agreeableness was associated with higher leader-follower imbalances (higher Q_{DCRP}), with more pronounced initiating behaviors, suggesting a task-sensitive effect. This can also indicate that one person allows (leads) the other to talk or be silent, by initiating those behaviors.

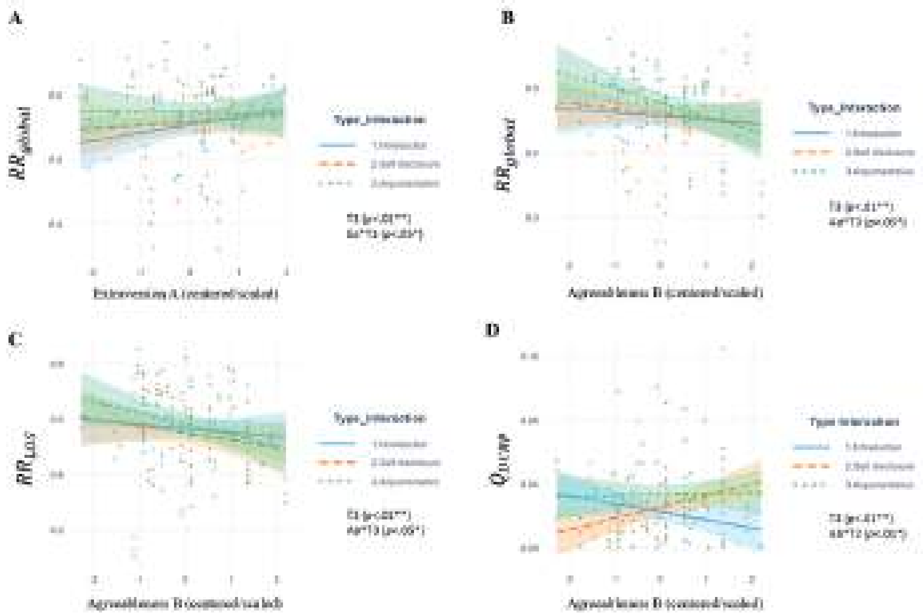
To further visualize the recurrence rates across different lags and leader-follower dynamics, Diagonal Cross-Recurrence Profiles (DCRPs) were plotted across the conversation topics (Figure 6A), which showed (descriptively) the highest recurrence percentage at lag-zero (line of synchrony) during the argumentative conversation, and the lowest recurrence rates during the self-disclosure task. This could indicate that during arguments, there would be a similarity of behavior, a strong and immediate interaction or response between the participants. It is also possible to see that during the introduction, the immediate effect, as captured by lag-zero, does not prominently show the asymmetries in the interaction dynamics. However, as the lags increase, asymmetries become more apparent. This could indicate that the interaction dynamics evolve over time, and asymmetries become more pronounced with increases in time lags.

When plotting the DCRPs considering personality traits (Figure 6B), a segmentation approach was employed, categorizing dyads into low and high personality trait scores using a threshold of -/+ 0.5 standard deviations (SD, see Method section). The profiles indicated that the highest RR_{LOS} (i.e., on the line of synchrony or at lag-zero) was observed in the dyads composed of low/high Agreeableness, which suggests a high degree of immediate synchronization of speech. Furthermore, as time lags increased, there was a subtle trend toward leading-follower dynamics, indicating that low/high Agreeableness dyads seemed to evolve with one individual taking the lead over time. This pattern was also observed in low and mixed agreeable dyads; however it was rather subtle. The lowest $\mathrm{RR}_{\mathrm{LOS}}$ was observed in introverted dyads, suggesting a lower level of immediate speech synchronization in interactions between introverted individuals. This segmentation and visualization has only descriptive purposes.

When modeling the effects of personality traits on the relative difference of Laminarity (LAM_{ARD}) the Extraversion scores of both conversational partners significantly predicted $\mathrm{LAM}_{\mathrm{ARD}}$ during the self-disclosure task (model 4, Table 5; β= -0.42, $t_{(100)}$= -2.32, p <.05), such that similarities in Extraversion (both for low and high Extraversion) were associated with lower LAM_{ARD} (Figure 7A). This suggests that the magnitude of the speech asymmetry in nonverbal interactional dominance decreased with personality similarity (in Extraversion) when self-disclosing, indicating symmetrical conversational dynamics or lower nonverbal interactional dominance. The asymmetries were higher in dissimilar dyads composed of introverted or extroverted individuals, in which case, one of the interacting partners tended to be more nonverbal interactionally dominant (in alignment with H3a). On the other hand, the Agreeableness level of both conversational partners predicted differences in $\mathrm{LAM}_{\mathrm{ARD}}$ during the argumentative task (β= 0.36, $t_{(100)}$= 2.74, p <.01; see Figure 7B). In this case, differences in the Agreeableness of both conversational partners (low/high) predicted lower asymmetries in nonverbal interactional dominance, and similarity in the dyadic composition, especially in high-agreeable individuals predicted higher asymmetries, which indicates higher nonverbal interactional dominance or greater influence of one interacting partner's behavior on the other (in opposition to H3b).

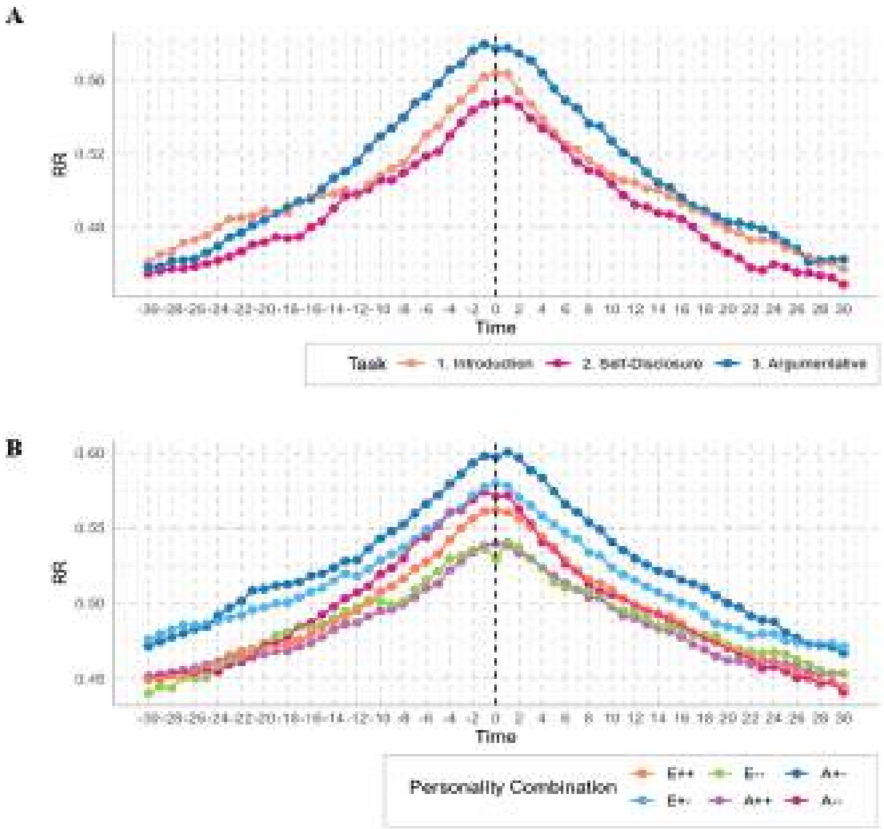
Finally, regarding Trapping Time $\mathrm{TT}_{\mathrm{ARD}}$, no significant effects were linked to personality traits. Only the type of conversation, self-disclosure, and argumentative significantly explained differences in $\mathrm{TT}_{\mathrm{ARD}}$ in both models of Extraversion (Table 5, Model 6) and Agreeableness (Table 6, Model 6). In both cases, the average duration of the asymmetries was expected to be higher and last longer during the self-disclosure and argumentative conversations than the introduction.

Figure 5. Effects of Extraversion on RR_{global} and Effects of Agreeableness on RR_{global}, RR_{LOS}, and Q_{DCRP}



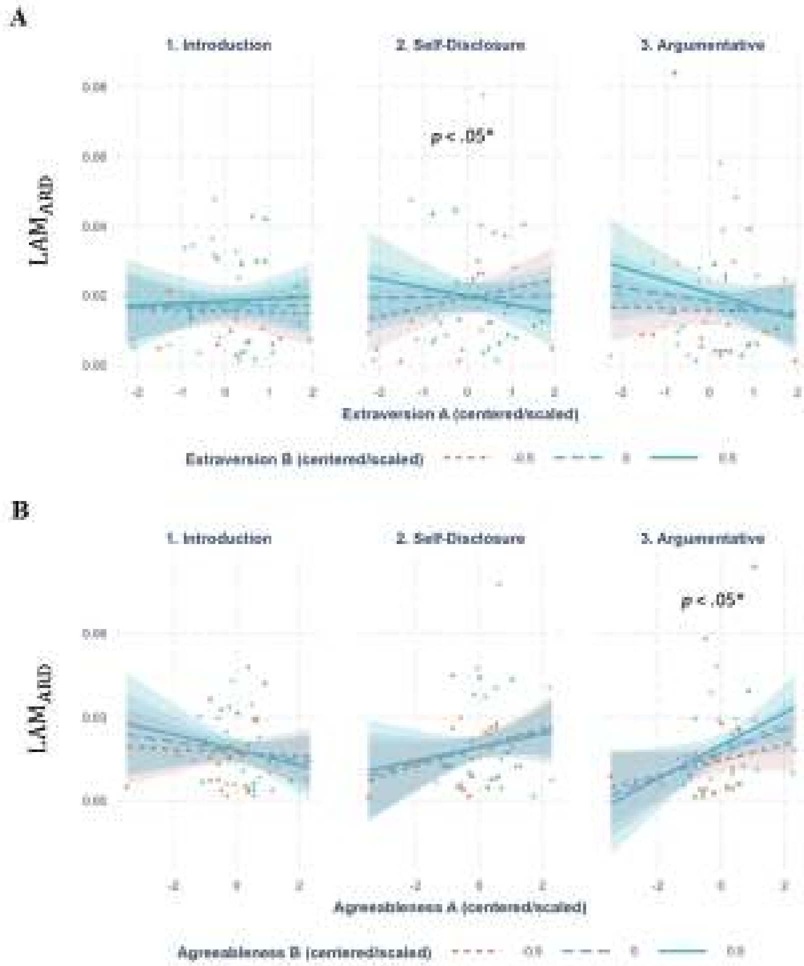
*Note: The plots represent the significant effects of the models of Extraversion and Agreeableness on the variables of speech synchronization (RR_{global}, RR_{LOS}) and nonverbal interactional dominance (Q_{DCRP}). The significant effects are, Panel A: [T3. Argumentative (**β**=.32, $t_{(100)}$=2.98, p<.01)], and [ExtraversionA*T3.Argumentative (**β**=-.22, $t_{(100)}$=-2.04, p<.05)]; Panel B: [T3.Argumentative (**β**=.34, $t_{(100)}$=3.23, p<.01)], and [AgreeablenessB*T3. Argumentative (**β**=-.26, $t_{(100)}$=-2.37, p<.05)]; in Panel C, [AgreeablenessB*T3.Argumentative (**β**=-.18, $t_{(100)}$=-2.01, p<.05)]; in Panel B, [T3.Argumentative (**β**=.50, $t_{(100)}$=2.81, p<.01)], and [AgreeablenessB*T2.Self-disclosure (**β**= 0.56, $t_{(100)}$=3.06, p<.01)].*

Figure 6. DCRPs by Topic and Personality Combination



Note: The plots represent the DCRPs of speech coordination (turn-taking match) by topic (Panel A) and by personality combination (Panel B). The zero on the "x" axis (dashed line) represents the line of synchrony (LOS) corresponding to lag-zero. The "y" axis indicates the RR (percentage of recurrence rate), representing speech synchrony (or coupling) between interacting partners during the complete 15-minute conversation. Lags to the sides of the line of synchrony line suggest that one behavior (i.e., speaking) is leading, and the other behavior (i.e., listening) is following after a certain time delay. This indicates a temporal pattern where one person initiates a turn, and the other responds after a specific duration (in seconds). In descriptive terms, in Panel A, task 3 exhibits the highest RR, and task 2, the lowest. In Panel B, the dyads composed of a person high and low in Agreeableness represent the highest RR and therefore, the strongest coupling; while the lowest RR is visualized in the dyads composed of two individuals with low scores on Extraversion. In panel B regarding dyadic personality combinations: "E++" and "A++"= high/high scores; "E--" and "A--"= low/low scores; "E+-" and "A+-"=low/high scores.

Figure 7. Effects of Extraversion and Agreeableness on LAM_{ARD}



*Note: The plots show the effects of Extraversion (Panel A) and Agreeableness (Panel B) on LAM_{ARD}. Panels A and B correspond to separate models (see Tables 5 and 6). In panel A, the effect of ExtraversionA*ExtraversionB * (2)Self-Disclosure is statistically significant (β=-.42, $t_{(100)}$=-2.32, p<.05). In panel B, the significant effects are AgreeablenessA* (3)Argumentative (β=.42, $t_{(100)}$=2.44, p<.05), and AgreeablenessA* AgreeablenessB*(3)Argumentative (β=.36, $t_{(100)}$=2.74, p<.01).*

In summary, as the Quotient of the Diagonal Cross Recurrence Profile (Q_{DCRP}) indicates, the argumentative task significantly affects the balance of interactions. During the argumentative conversations higher imbalances in leader-follower dynamics were observed, with one partner tending to speak first while the other follows. Conversely, the self-disclosure task predicts more balanced interactions than introductions, particularly for individuals with higher Agreeableness scores. However, higher Agreeableness is associated with higher imbalances in leading-following dynamics during self-disclosure, suggesting a task-sensitive effect. Extraversion and Agreeableness exhibit differential effects on interaction dynamics across tasks. Similarities in Extraversion between conversational partners are associated with lower speech asymmetry during self-disclosure, indicating symmetrical conversational dynamics or lower nonverbal interactional dominance. Conversely, dissimilar dyads, specially composed of extroverted and introverted individuals, show higher asymmetries. Agreeableness influences asymmetries in nonverbal interactional dominance during argumentative tasks, with similarities in Agreeableness predicting lower asymmetries, while high Agreeableness predicts higher asymmetries or greater nonverbal interactional dominance. The DCRPs (Figure 6) visually depict the interaction dynamics, showing the highest recurrence percentage at lag-zero during argumentative conversations and the lowest during self-disclosure tasks. Segmentation based on personality traits reveals immediate speech synchronization in low/high Agreeableness dyads and subtle leading-follower dynamics over time. Regarding the average duration of nonverbal interactional dominance, personality traits do not significantly affect the duration of the influence of one system over the other (TT_{ARD}), but the type of conversation significantly influences it, with self-disclosure and argumentative conversations leading to higher and longer-lasting asymmetries in nonverbal interactional dominance compared to introductions. The findings suggest that conversational topics and personality traits, particularly Extraversion and Agreeableness, play significant roles in shaping interaction dynamics.

3.4. Perception of the interactions (appraisals)

Finally, we modeled the effects of personality differences (Extraversion/Agreeableness separately) of both conversational partners and our variables of speech synchronization (RR_{LOS}, Q_{DCRP}, and LAM_{ARD}, in separate models) on each of the appraisals reported by the participants after their conversations (see method section for more details about each model). Table 2 contains the variables we used to assess the perception of the interactions i.e. appraisals. We corrected the p-values for multiple-hypothesis testing (using the Benjamini-Hochberg procedure, 1995). Tables with all models and figures with significant effects can be consulted in the supplementary materials.

3.4.1. Inclination for communication (need to communicate with partner)

Extraversion scores without interacting with other variables predicted a higher need to communicate with the interacting partner (β= 0.10, p<.05). Higher Extraversion levels of both interacting partners and more speech synchronization (RR_{LOS}) were predictive of increased perceived "need to communicate" (β= 0.11, p<.01), indicated by increased synchronization of speech across the line of synchrony (model 1, Table S1, Figure S1.A). In this context, speech synchronization (RR_{LOS}) suggests a greater reciprocity and attunement in terms of speech-silence matching, more time spent talking, fewer pauses, silences, and interruptions. Introverted dyads predicted the lowest inclination for communication overall. And, in the case of mixed extroverted dyads (low/high Extraversion), when speech synchronization (RR_{LOS}) decreased, the need for communication was observed to increase. In the case of Agreeableness, the interaction effect between the scores on Agreeableness of both conversation partners predicted decreases in the need for communication for low agreeable individuals in the model of LAM_{ARD} (β= -0.08, p<.05) (model 1, Table S5, Figure S1.B); whereas the presence of at least one agreeable individual in the dyad (mixed dyads), predicted increases in the inclination for communication. There were no specific significant effects of speech variables and Agreeableness.

3.4.2. Using partner's behavior as a guide for own behavior

Asymmetries in nonverbal interactional dominance could be observed in the model of relative differences in Laminarity (LAM_{ARD}), where lower Extraversion scores associated with more perceived behavioral adjust to the partner cues (compared to extroverts, β= -0.14, p<.01) (model 2, Table S2, Figure S2.A). Extraversion scores (of one interacting partner) and LAM_{ARD} showed an interaction effect, as lower scores on Extraversion associated with higher asymmetries (higher LAM_{ARD}) and predicted more perceived behavioral use of the partner cues (β= 0.27, p<.05). There was also a three-way interaction where Extraversion scores of both interacting partners (β= 0.23, p <.05) predicted lower symmetry (lower LAM_{ARD}) in mixed dyads. The perceived alignment to the partner cues was predicted to increase, especially among introverts, whereas during high asymmetry (high L LAM_{ARD}), participants tended to align their behavior to the partners' behavior in mixed dyads (low/high) and extroverted dyads, which suggests that a more pronounced nonverbal interactional dominance in such dyads was reflected in the report of one of them using the partners' behavior as a guide of the own behavior.

In the model of Agreeableness with Laminarity (LAM_{ARD}) as predictor, the interactive three-way effect (β=0.27, p<.05) suggested that during lower nonverbal interactional dominance (lower LAM_{ARD}) highly agreeable dyads were more likely to use the partners' behavior as a guide for the own behavior (model 2, Table S5, Figure S2.B). In mixed agreeable dyads, however, the interactive effects suggest that agreeable individuals exhibited initiating behaviors, whereas disagreeables tended to align their behavior to the partner cues when LAM_{ARD} was higher (nonverbal interactional dominance asymmetries). These results suggest that highly agreeable dyads tend to use their partners' behavior and that is linked to symmetrical interactions (lower LAM_{ARD}). On the other hand, agreeable individuals may tend to take the initiative when interacting with disagreeable partners, while disagreeable individuals align their behavior with partner cues when LAM_{ARD} is higher (nonverbal interactional dominance asymmetries).

3.4.3. Attempts to lead the conversation

The effect of Agreeableness of at least one conversational partner and the (im) balances in the conversation (Q_{DCRP}) significantly predicted the perceived attempt to lead the conversation. Increases in imbalances in leading-following dynamics (Q_{DCRP}) predicted increases in the perceived attempt to lead the conversation by low agreeable individuals (β=0.17, p<.05). There was a three-way interaction between Agreeableness scores of both conversational partners and the balance of the interaction (Q_{DCRP}), where in dissimilar dyads (low/high), higher imbalances (Q_{DCRP}) predicted increases in the perceived attempt to lead the conversation by low agreeable individuals (β= -0.32, p<.05) (model 3, Table S6, Figure S3).

3.4.4. "Smooth, natural, and relaxed" conversations

Agreeableness positively predicted the report of smooth, natural, and relaxed conversations when considering the personality trait without interacting with other variables (p<.05) (model 6, Table S4, Figure S4.A). However, the interaction of Agreeableness and speech synchronization (RR_{LOS}) was negatively related to the perception of the conversation as smooth, natural, and relaxed (β= -0.35, p<.05). This effect suggests that as the interaction between Agreeableness and speech synchronization was higher –thus more attunement of speech-silence turns, more time spent talking, fewer pauses, silences, and interruptions– there was a corresponding decline in the perception of the conversation as smooth, natural, and relaxed. This may indicate a trade-off effect. In other words, while Agreeableness and speech synchronization (at lag-zero) might enhance certain aspects of a conversation (e.g., interpersonal attunement), they could also make it feel less relaxed and natural, which will be addressed in more detail in the discussion section.

3.4.5. Felt accepted and respected by partner

Overall, a main effect indicated that higher Extraversion scores were associated with increases in the perception of being accepted and respected by the interacting partner (β= 0.25, p<.01); whereas lower scores on Extraversion predicted decreases in this perception of being accepted/respected (model 9, Table S2). No effects were found for

Agreeableness and speech synchronization variables. This could imply that these factors might not directly influence the feeling of acceptance and respect in a conversation, or their effects might be more subtle or complex.

3.4.6. Desire to interact more with partner in the future

Only Extraversion and speech synchronization (RR_{LOS}) such as speech-silence attunement, reciprocity, and fewer silences and interruptions, increased participants' willingness for future interactions (model 10, Table S1, Figure S4.B). High Extraversion scores of at least one interacting partner and increases in speech synchronization predicted a higher post-conversational desire to interact in the future (β = 0.46, p<.01). This implies that both personality traits and the dynamics of the conversation itself can influence the desire for future interactions.

3.4.7. Enjoyment of the interaction

High Extraversion (of at least one interacting partner) and higher speech synchronization (RR_{LOS}) were associated with an increased enjoyment of the interactions (β = 0.28, p <.05) (model 11, Table S1). Conversely, for introverted individuals, higher speech synchronization predicted decreases in enjoyment. The effect of both conversational partners was significant as well (three-way interaction), but highly extroverted dyads enjoyed conversations with a higher speech synchronization more (β =0.42, p <.05) (Figure S5.A). In more dissimilar dyads (extroverted/introverted) lower speech synchronization was associated with increased enjoyment. In the case of the Extraversion of both interacting partners and the asymmetries in nonverbal interactional dominance (LAM_{ARD}, the three-way interaction), lower asymmetries and high scores on Extraversion of both interacting partners predicted increased enjoyment (β = -0.25, p <.05) (model 11, Table S2, Figure S5.B). When the asymmetries (LAM_{ARD}) increased, the enjoyment was predicted to increase as well for mixed dyads (introverted/extroverted). Furthermore, introverted dyads were associated with decreased enjoyment during the conversation (compared to the other participants), independent of other interpersonal speech dynamics in the conversation. In the case of balance in leader-follower dynamics (Q_{DCRP}), a three-way interaction indicated that increased imbalances –an interacting partner tended to temporally initiate/lead or act first, either speaking or being silent– were predictive of enjoyment in extroverted dyads (β =0.44, p <.05); whereas in mixed dyads (introverted/extroverted), more balanced interactions (Q_{DCRP}) were predictive of increases in enjoyment (model 11, Table S3, Figure S5.C).

3.4.8. Perceived partner as likable

The main effect of Extraversion indicated that increases in this trait were positively associated with increases in the report of liking the conversational partner (β = 0.14, p<.01) (model 14, Table S1, Figure S6.A). Similarly, the interactive effect of Extraversion scores and increases in speech synchronization (RR_{LOS}) predicted an increased report of liking the conversational partner (β = 0.49, p<.05). On the other hand, decreased scores on Extraversion and lower values of speech synchronization predicted increases in liking the other person. Similarly, the three-way effect between the Extraversion scores of both partners and speech synchronization suggested that in extraverted dyads, increases in speech synchronization were associated with liking the interacting partner to a greater extent; whereas in mixed dyads (introverted/extroverted), decreases in speech synchronization –which indicates the presence of silences as well– were associated with liking the other person (β =0.21, p <.05) (model 14, Table S1, Figure S6.B). These effects may indicate that introverted and extroverted individuals valued different aspects of the conversation. Extraverts seemed to appreciate a more dynamically synchronized conversation, while introverts may find value in moments of silence or pauses during interactions. The distinction in preferences between introverted and extroverted individuals is particularly salient in mixed dyads.

3.4.9. Perceived partner as empathic and understanding

Finally, increased Extraversion scores were associated with increases in the perception of the conversational partner as empathic and understanding (main effect, β =0.02, p <.05). And, the interaction between Extraversion and the nonverbal interactional dominance or asymmetries in the interaction (LAM), indicated that lower asymmetries and higher Extraversion scores predicted increases in the perceived empathy and understanding; whereas lower scores in Extraversion and increases in the asymmetries, were predictive of increased perceived empathy and understanding (β =-0.31, p <.05) (model 15, Table S2, Figure S7). This can reflect differences in the appraisals of interpersonal dynamics of speech in the conversation by personality differences as will be discussed. For the rest of the appraisal variables, no significant effects linked to personality traits were found after correcting for multiple hypotheses testing, but all the results can be found in the supplementary materials.

Overall, these findings highlight the relationship between personality traits, speech synchronization, and the perception of interaction dynamics. They underscore the importance of considering individual differences in communication styles and patterns when assessing the quality of social interactions.

4. Discussion

This study was conducted to achieve four goals. First, exploring the effect of high-level constraints (here: conversational topics) on interpersonal speech synchronization, leading-following dynamics, and nonverbal interactional dominance in dyadic conversations (1). In the next two goals we aimed to explore how the interpersonal speech synchronization structures were related to the socially relevant personality traits of Extraversion and Agreeableness of the interacting partners. In particular, exploring how these personality traits were related to synchronization of speech (2), as well as leader-follower dynamics and nonverbal interactional dominance (3). Lastly, we aimed to explore the effect of synchronization of speech, leader-follower dynamics, nonverbal interactional dominance, and personality traits in the appraisals of the interactions reported by the conversational partners (4). Following these goals, our key findings are discussed below, considering theoretical implications, limitations, and future directions.

4.1. Interpersonal speech synchronization and conversation topic

We expected that different conversational topics explained differences in our variables of speech synchronization (RR_{global}, RR_{LOS}) (H1a), leader-follower dynamics (Q_{DCRP},) and nonverbal interactional dominance (LAM_{ARD}, and TT_{ARD}) (H1b). We anticipated differences in speech dynamics between the self-disclosure and argumentative conversations compared to the introduction. Conversational topics indeed predicted differences in global speech synchronization (RR_{global}), but only in terms of more synchronization during the argumentative conversation versus the introduction part. Regarding leader-follower dynamics and nonverbal interactional dominance, our hypothesis (H1b) about the role of conversational topics was supported in the self-disclosure (TT_{ARD}) and argumentative conversations (Q_{DCRP}, TT_{ARD}). Differences in high-level conversational constraints i.e. the topics were aligned with our expectations and the literature on interpersonal synchronization. Consistently, studies indicate that dynamic properties of interpersonal interactions (interpersonal speech synchronization) are shaped by situational constraints, or in other words, are soft-assembled (Fusaroli et al., 2014), and depend on the context where the encounter unfolds. This interplay aligns with the perspectives of language and joint action as complex adaptive systems (e.g., Ellis & Larsen-Freeman, 2009; Paxton & Dale, 2017; Tschacher et al., 2018; Arellano-Véliz et al., 2024a). Similarly, situational factors are also relevant in individual settings, affecting movement and self-organizing dynamics (Arellano-Véliz et al., 2024b).

The role of the high-level constraints (e.g., conversation topics) in speech synchronization can vary as it flexibly adjusts to casual encounters, bonding/affiliating, or competitive goals (Paxton & Dale, 2017). Previous research showed that patterns of nonverbal interactional dominance and balance can affect the quality of the interactions and interacting partners tend to be sensitive to distinct cues in the conversation, which can be functional to interpersonal goals (Reuzel et al., 2014). In the case of this study, the effect of the argumentative conversation on global synchronization of speech was significantly higher compared to the introductory conversation, and the same was true for leader-follower dynamics and nonverbal interactional dominance, where the asymmetries in the conversation were larger during this conversation. Increased interpersonal synchronization during specific conversation topics has been observed in competitive settings previously (e.g., Tschacher et al., 2018; Arellano-Véliz et al., 2024a). Other studies reported that in-phase (simultaneous) bodily synchronization decreased during arguments (Paxton & Dale, 2013). However, as mentioned in the introduction, the concepts of functional interpersonal synchronization and interpersonal speech synchronization involve compensatory dynamics (that do not necessarily unfold simultaneously) and support the emergence of functions or the achievement of goals (Nowak et al., 2017).

Likewise, we operationalized speech synchronization as the reciprocity of the interacting partners' nonverbal behaviors, focusing on turn-taking coordination and a conversational rhythm instead of a simultaneous performance (Reuzel et al., 2013). Reciprocity is key in argumentative conversations, where exchanges in interpersonal dynamics will facilitate the emergence of a dynamic and swift interplay of bidirectional exchange of arguments. Furthermore, our observation that the relative difference in trapping time (TT_{ARD}) was larger during the self-disclosing and argumentative conversations, can indicate sustained influence by one interacting partner for an extended period. This nonverbal interactional dominance can mean that one partner's speech or silence episodes tended to "trap" the other partner in longer episodes of speech or silence, and this can be indicative of providing the other partner with the opportunity –or the affordance– to display such behavior by acting first (Worgan & Moore, 2010). Even though it can indicate more "control" in the dynamics, this can also afford and facilitate a reciprocal interaction when self-disclosing personal information. According to previous research, therapists use their nonverbal interactional skills to intensify the attunement with clients by leading in the use of turn-taking and driving dynamical synchronization of speech (Reuzel et al., 2014). This type of behavior might have been displayed by some interacting partners to improve the communicational rhythm when self-disclosing, which might involve longer interpersonal speech synchronization.

Conversational topics were unrelated to speech synchronization across the line of synchrony (RR_{LOS}) and one of the measures for nonverbal interactional dominance, Laminarity (LAM_{ARD}), which may be due to our modest sample size, and indicates that these findings should be replicated in future studies. In general, the variable of global synchronization of speech is more robust as it considers all possible lags in the conversation. It gives a general overview of the interpersonal speech synchronization and patterns across the conversation (Reuzel et al., 2014). In this sense, some responses and exchanges might be time-sensitive and be visible at longer lags rather than simultaneously or very close in time, as indicated by speech synchronization across the line of synchrony (RR_{LOS}), which represents swift dynamics.

4.2. Personality traits, speech synchronization, and nonverbal interactional dominance

We argued that the personality traits of each conversational partner interact and promote the emergence of interpersonal speech dynamics at the dyadic level. In particular, we expected that the dimensions of Extraversion and Agreeableness –the key social traits– would explain part of the variability in speech synchronization (H2), leader-follower dynamics, and nonverbal interactional dominance (H3), based on our previous work on interpersonal dynamics of body motion (Arellano-Véliz et al., 2024a).

Extraversion scores were associated with increased speech synchronization (RR_{global}) while introverts synchronized less (H2a). Extraverted individuals showed more synchronized communication across multiple time lags (not just at lag-zero as indicated by RR_{LOS}), and across all conversational topics, which illustrates that interpersonal speech dynamics in highly extroverted individuals were more context-independent. Extroverts are defined as highly socially, gregarious, and outgoing individuals (Costa & McCrae, 1995), for whom social encounters are rewarding in themselves, which promotes higher intersubjective attunement (Stern, 1985/2018; Harris et al., 2017). Introverts exhibited the lowest synchronization of speech, especially during the introductory conversation. Introverted individuals varied in synchronization across topics, as argumentative conversations exhibited the highest degree of synchronized communication. These results align with the social reactivity hypothesis that extraverts get more pleasure from social interactions, and, therefore, have more drive to engage in them, compared to introverted individuals (Lucas & Diener, 2001). Generally speaking, introverts prefer solitude and tend to be more comfortable with their inner worlds, thoughts, and feelings than extroverts (Burger, 1995; Tuovinen et al., 2020).

Regarding the composition of our dyads, we expected that when both interacting partners were extroverted or at least one of them was extroverted, this would lead to increased speech synchronization (H2b). In this case, the presence of at least one extroverted individual in the dyads led to increased synchronization, which might be relevant to facilitating social interactions for introverts, as it might boost their social engagement (Tuovinen et al., 2020). The interactive effect of both conversational partners was not significant in the models of speech synchronization (RR_{global} , and RR_{LOS}), only the individual effect of the trait Extraversion in global speech synchronization (RR_{global}). Therefore, the presence of at least one extravert played a more relevant role in the interpersonal dynamics.

We expected high agreeable scores to associate with dyadic coupling and increased speech synchronization, and inverse expectation for low-agreeable (or "disagreeable") dyads (H2c). Speech synchronization was predicted to be slightly lower for agreeable individuals. Dyadic composition was expected to affect speech synchronization, especially the presence of a disagreeable individual in the dyad, but no support was observed (H2d). However, the task sensitivity effect we predicted regarding the argumentative conversation was supported (H2e) as low Agreeableness associated with higher speech synchronization during the argumentative conversation (RR_{global} and RR_{LOS}). We argued that this effect could be functional to goal achieving in competitive settings by low-agreeable individuals (e.g., DeYoung, 2015), and this could be observed in interpersonal speech dynamics by highly responsive and swift interactions in the conversation. However, these dynamics might not be positive for the intersubjective attunement of the interacting partners, since the literature suggests that low-agreeable individuals exhibit poor social relationships (Anderson et al., 2020), low concern for others' needs and desires, and less efficient social information processing (e.g., DeYoung, 2010).

Concerning leader-follower dynamics and nonverbal interactional dominance, we expected that higher scores of Extraversion would be associated with asymmetries in the speech dynamics when interacting with introverts, possibly because of the emergence of leading (initiating) and influencing tendencies (H3a). This was observed only with asymmetries reflected by the relative difference of Laminarity (LAM_{ARD}) during the self-disclosing conversations, where personality similarity fostered symmetric interpersonal speech dynamics, and personality dissimilarity accentuated asymmetries between interacting partners. It is possible that extroverted individuals took a leading and initiating role within the conversation when interacting with introverted partners allowing for longer periods of interactional attunement.

We also expected more balanced leading-following dynamics for agreeable individuals, in contrast to disagreeable individuals, where the latter might predict larger imbalances in the interactions (H3b). Results supported this hypothesis when looking at the diagonal cross-recurrence profiles (through Q_{DCRP}) during the introduction. We found that low-agreeable individuals exhibited a larger imbalance in leader-follower when introducing themselves and lower when self-disclosing. Highly agreeable individuals predicted the opposite patterns, with lower imbalance when introducing themselves and higher when self-disclosing, which indicates that agreeables might have taken the lead during this conversation. When looking at the asymmetries in nonverbal interactional dominance (LAM_{ARD}), the argumentative conversation elicited higher nonverbal interactional dominance, especially in high-agreeable individuals and mixed agreeable dyads (agreeable/disagreeable). In this sense, as mentioned before, Agreeableness is a social trait characterized by a tendency towards cooperation, altruism, and aligning their needs with those of others (DeYoung, 2015; Hovhannisyan & Vervaeke, 2022). These patterns of leading behavior and nonverbal interactional dominance suggest that when self-disclosing, highly agreeable partners tend to take the initiative more, in a prosocial way. This may be especially visible in mixed dyads, facilitating attunement to those patterns and possibly fostering a reciprocal and cooperative conversational dynamic (Worgan & Moore, 2010). The same could be said for the argumentative conversation, where highly agreeable individuals may have tended to “dominate” the conversation, promoting longer episodes of attunement. Remember that dominance in this context should not be interpreted with the negative connotation it often has. The observed tendency might be linked to the higher metacognitive capacity in agreeable individuals, described by a better understanding of others’ needs, intentions, and desires (DeYoung, 2010).

4.3. Perception of the interaction (appraisals), interpersonal speech dynamics, and personality traits

Higher degrees of dyadic speech synchronization (H4a) and symmetrical and balanced interactions (H4b) were predicted to increase positive post-conversational appraisal. Extroverted (H4c) and agreeable (H4d) individuals were expected to appraise the interaction as more positive after more synchronized interactions. The results obtained exhibited differentiated effects regarding the dyadic constitution and interpersonal speech dynamics.

First, we observed a logical connection between the interpersonal speech dynamics in the conversation indicated by the variables extracted from the time series analyses and the appraisals reported by the participants. In the case of Extraversion, this trait consistently predicted positive perceptions of the interaction as expected. When exploring the role of speech synchronization in the conversation, we observed that high scores of Extraversion, and increased synchronization of speech (RR_{LOS}), were consistently related to positive appraisals such as perceptions of the conversation as smooth/natural/relaxed, desire to interact in the future, enjoyment, liking the conversational partner, and an inclination to communicate. These results underscore the relevance and value of attuned and swift conversations for highly extroverted individuals. RR_{LOS} reflects swift turn-taking in the conversation, that is, very attuned conversations with few silence episodes (i.e. both not speaking) and interruptions (i.e. both speaking at the same time). In this sense, as we observed a different effect for introverts, it is possible that they valued the presence of silences and pauses more than ongoing attunement and swift dynamics. These results align with H4a and H4c.

On the other hand, increases in nonverbal interactional dominance (i.e. increases in LAM_{ARD}) predicted perceptions such as using the interaction partner’s behavior as a guide, especially in introverts, which reflects an attempt to align to the partners’ cues. Higher asymmetries in nonverbal interaction dominance (LAM_{ARD}) led to increased enjoyment when mixed extroverted dyads interacted. In this sense, it may be that nonverbal interactional dominance could have promoted a better quality in the interactions in these dyads, presumably by affording and facilitating opportunities for sustaining interactional attunement.

The effects of interpersonal speech dynamics in positive appraisals can indicate a higher intersubjective attunement and relatedness (Stern, 1985/2018). Previous studies on undergraduate students showed that Extraversion predicted 4 years later their subjective well-being (Harris et al., 2017). In particular, self-reported and peer-reported positive social experiences such as feelings of belonging and larger size of social networks are highly relevant for these young populations. It would be relevant to consider that introverted individuals can also be rewarded by interpersonal interactions when they interact with individuals dissimilar to them in terms of personality. In this sense, they may benefit from a certain degree of guidance/leading and initiating behaviors (someone who creates social opportunities for them) when sustaining social interactions (Tuovinen et al., 2020). Furthermore, introverts might value slower conversations, with more pauses and silences as their need for social stimulation is lower than for extroverts (DeYoung, 2015; Hovhannisyan & Vervaeke, 2022).

On the other hand, we observed that in highly agreeable dyads (similar) agreeable individuals tended to use the partner's behavior as a guide, which was observed also in the form of lower asymmetries in nonverbal interaction dominance (LAM_{ARD}). Agreeableness is thought to play a significant role in fostering interpersonal attunement during the conversation (cf. Anderson et al., 2020). These adjustments and attunement to the partner's behavior can be indicative of high dyadic and nonverbal coupling as well. In addition, contrary to our expectations (H4d), increased speech synchronization and Agreeableness were predictive of decreased perceived naturality in the conversations. We could argue that there may be a trade-off effect to sustaining synchronized communication –in the form of smooth turn-taking dynamics, fewer episodes of silence, and overall more time of speech– where highly agreeable individuals achieved this communicational rhythm without feeling natural. It can be also possible that agreeable individuals need more time to respond (more lags) or value episodes of silence as well. Similarly, previous studies have indicated that to sustain interpersonal synchronization, there is a trade-off effect where the self-regulation of affect decreases as the interacting partners adapt to each other (Galbusera et al., 2019). It would be plausible to think that the drive of Agreeableness towards altruism, cooperation, and social harmony (DeYoung, 2015) could have played a role in a greater effort to sustain these smooth interpersonal speech dynamics without experiencing the social encounter as inherently pleasant. Furthermore, we also observed a task sensitivity in both Extraversion and Agreeableness, that underscores the situational context in shaping interpersonal communication.

5. Conclusion

Overall, our results emphasize the dynamic interplay between the personality traits Extraversion and Agreeableness, situational constraints (conversation topics), interpersonal speech dynamics –synchronization, leader-follower dynamics, and nonverbal interactional dominance–, as well as the subjective experiences emerging from social interactions. Personality traits exhibited relevance in speech dynamics and appraisals, and differences in terms of the dyads' constitutions were observed. Generally, we observed that extroverted individuals engaged in more synchronized communication across various conversational topics, contrary to introverts. Besides, interpersonal speech synchronization seemed to foster intersubjective attunement and positive appraisals in extroverts. Increased speech synchronization and Agreeableness were predictive of decreased perceived naturality in the conversations, suggesting a potential trade-off effect. In terms of the methods employed, we were able to observe how situational constraints and personality traits were predictive of interpersonal speech dynamics in the conversations and appraisals. The nonlinear time-series techniques employed exhibited a useful and robust tool for studying interpersonal dynamics in conversations. Our results support the use of dynamical approaches to, not only understanding interpersonal communication, but also its relation to psychological constructs.

6. Limitations, strengths, and future directions

It is relevant to acknowledge the limitations of our study, in particular, the modest sample size, which needs to be considered in the generalizability of our results. In this regard, some significant effects became non-significant after multiple testing solutions, and therefore, were not discussed. Moreover, our sample predominantly comprised women, thus limiting the ability to draw comparisons across genders. To address this limitation and enhance the generalizability of our findings, future research should aim to utilize larger and more diverse samples. This will allow for the replication and extension of our results across a broader demographic spectrum.

The nonlinear time series analysis methods allowed us to capture subtle and robust interpersonal dynamics that might have not been observed otherwise, which we consider a strength in our experimental design. In this sense, we recognize a promising toolbox to be incorporated to a greater extent in the study of interpersonal dynamics and personality research.

Finally, we understand that we studied a dimension of speech that did not consider the context of the conversations, the content of the utterances, and other personality traits. Instead, we focused on the interpersonal dynamics extracted from a specific set of interpersonal speech dynamics –turn-taking behaviors– and the most relevant "social" personality traits. In this sense, content is highly relevant to understanding these interpersonal dynamics so other traits can be relevant. Therefore, future studies may need to consider the synchronization of speech and interpersonal speech dynamics at the content level. This will expand our comprehension of interpersonal dynamics, communication, and personality traits.

7. Acknowledgments

We thank all participants who took part in the study. We acknowledge Mark Span (Ph.D.) for technical support on the experimental setup and software adaptation, and Christin Khafaji Zadeh for her valuable support on coding the data. Nicol Arellano-Véliz was supported by Agencia Nacional de Investigación y Desarrollo (ANID), Gobierno de Chile (Ph.D. Scholarship 72200122), Bertus Jeronimus by NWO-Veni 016.195.405. Ramón Castillo was supported by ANID, Gobierno de Chile (FOVI210047; FONDEQUIP-EQM 190153) and Programa de Investigación Asociativa en Ciencias Cognitivas (RU-158-2019), Universidad de Talca, Chile.

8. Ethics statement and conflict of interest

This study was approved by the Ethical Committee for research with human participants of the Faculty of Behavioural and Social Sciences, University of Groningen, code PSY-1920-S-0525. The authors declare no conflict of interest related to this research, authorship, or publication.

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11. Data availability

Further materials such as data and scripts can be accessed at https://doi.org/10.17605/OSF.IO/53NZ2

Table 4. Mixed-effects models predicting CRQA, DCRP and aCRQA measures from tasks with 50 dyads (Ni) (100 participants) and 150 observations (Nt), (50i * 3 tasks)

	Model 1. RR_{global}		Model 2. RR_{LOS}		Model 3. Q_{DCRP}		Model 4. LAM_{ARD}		Model 5. TT_{ARD}	
Predictors	**Estimate B (SE)**	**t**	**Estimate B (SE)**	**t**	**Estimate B (SE)**	**t**	**Estimate B (SE)**	**t**	**Estimate B (SE)**	**t**
Intercept	0.456 (0.008)	**53.99*** **	0.564 (0.021)	**28.69*** **	0.022 (0.002)	**7.43*** **	0.017 (0.002)	**8.32*** **	0.111 (0.017)	**6.62*** **
Task 2	0.004 (0.007)	0.61	-0.015 (0.013)	-1.23	0.004 (0.003)	0.97	0.002 (0.002)	0.69	0.052 (0.021)	**2.43***
Task 3	0.019 (0.007)	**2.86** **	0.014 (0.126)	1.08	0.011 (0.004)	**2.92** **	0.001 (0.002)	0.29	0.046 (0.021)	**2.14***
Random Effects										
ICC	0.70		0.80		0.70		0.27		0.19	
Marg. R^2/ Cond. R^2	0.02/0.70		0.01/0.80		0.01/0.70		0.002/0.27		0.04/0.22	
AIC	-461		-247		-693		**-811**		-189	

*Note: Significance was indicated as * $p < .05$. ** $p < .01$,***$p <.001$. N_i= number of participants. N_t= total; number of observations, which was = 150 (50 dyads * 3 tasks). SE= Standard Error. Task 2 = Self-disclosure. Task 3 = Argument. Task 1 (Introduction) was considered the baseline in the models. AIC = Akaike's Information Criterion (lower values indicate better fit). ICC = Intra-class Correlation Coefficient. see Table 1 for definitions. RR_{global}= Recurrence Rate Global, RR_{LOS}= Percentage of Speech across the line of Synchrony (lag-zero), Q_{DCRP} = Quotient Diagonal Cross-Recurrence Profile (absolute), LAM_A= anisotropic Laminarity, TT_A= anisotropic Trapping Time, LAM_{ARD}= Relative difference of anisotropic Laminarity, TT_{ARD}= Relative difference of anisotropic Trapping Time. Definitions of each measure can be found in Table 1.*

Table 5. Mixed-effects models predicting CRQA, DCRP, and aCRQA measures from Extraversion and task. Ni=50 dyads (100 participants); Nt=150 observations (50i*3 topics)

	Model 1. RR_{global}			Model 2. RR_{LOS}			Model 3. Q_{DCRP}			Model 4. LAM_{ARD}			Model 5. TT_{ARD}		
Predictors	B	β	t	B	β	t	B	β	t	B	β	t	B	β	t
Intercept	0.45	-0.15	**54.34*** **	0.56	-0.01	**28.8*** **	0.02	-0.22	**7.70*** **	0.02	-0.07	**8.55*** **	0.11	-0.26	**6.65*** **
Extraversion "A" (E_A)	0.01	0.21	1.45	0.03	0.21	1.44	-0.00	-0.01	-0.06	0.00	0.01	0.05	0.00	0.02	0.14
Extraversion "B" (E_B)	-0.01	-0.21	-1.44	-0.03	-0.18	-1.22	0.00	0.03	0.23	0.00	0.19	1.35	0.01	0.08	0.57
T2. Self-disclosure	0.00	0.07	0.69	-0.01	-0.10	-1.09	0.00	0.12	0.70	0.00	0.18	1.10	0.05	0.44	**2.51***
T3. Argumentative	0.02	0.32	**2.98****	0.01	0.09	1.04	0.01	0.54	**3.02****	0.00	0.09	0.57	0.05	0.37	**2.10***
E_A * E_B	0.01	0.18	1.2	0.02	0.12	0.76	-0.00	-0.13	-0.86	0.00	0.06	0.44	-0.00	-0.03	-0.19
E_A * Task 2	-0.01	-0.13	-1.15	-0.01	-0.06	-0.62	0.00	0.16	0.88	0.00	0.00	0.01	0.02	0.14	0.78
E_A * Task 3	-0.01	-0.22	**-2.04***	0.00	0.00	0.05	-0.00	-0.14	-0.76	-0.00	-0.14	-0.85	0.00	0.00	0.01
E_B * Task 2	0.01	0.20	1.77	0.02	0.12	1.28	-0.01	-0.34	-1.82	-0.00	-0.16	-0.93	-0.00	-0.03	-0.18
E_B * Task 3	0.00	0.02	0.17	0.02	0.12	1.33	-0.00	-0.09	-0.46	0.00	0.14	0.81	0.00	0.04	0.21
E_A*E_B*Task 2	0.00	-0.04	-0.36	-0.01	-0.09	-0.91	0.01	0.36	1.82	-0.01	-0.42	**-2.32***	-0.01	-0.11	-0.55
E_A*E_B*Task 3	0.00	-0.04	-0.30	0.00	0.03	0.28	-0.00	-0.04	-0.20	-0.00	-0.30	-1.66	0.00	0.04	0.20
Random Effects															
ICC	0.80			0.80			0.13			0.28			0.18		
Marg. R^2/Cond. R^2	0.063/0.725			0.050/0.805			0.106/0.218			0.094/0.346			0.063/0.235		
AIC	-379.1			-175.4			-597			**-713.2**			-118.3		

Note: B=unstandardized raw estimate; ***β****=beta weights (standardized). * indicates $p < .05$. ** indicates $p < .01$. ***indicates $p < .000$. p-values were BH corrected (Benjamini & Hochberg, 1995) FDR procedure. Task 1 (Introduction) is the baseline. Task 2 = Self-disclosure; Task 3 = Argumentative. E=Extraversion. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered/scaled. RR_{global}= Recurrence Rate Global, RR_{LOS} = Percentage of Speech across the line of Synchrony (lag-zero), Q_{DCRP}= Quotient Diagonal Cross-Recurrence Profile (absolute), LAMA= anisotropic Laminarity, TT_A= anisotropic Trapping Time, LAM_{ARDf}= Relative difference of anisotropic Laminarity, TT_{ARD}= Relative difference of anisotropic Trapping Time. Definitions of each measure can be found in Table 1.*

Table 6. Mixed-effects models predicting CRQA, DCRP and aCRQA measures from Agreeableness and task. N_i=50 dyads (100 participants); N_t=150 observations (50i * 3 topics)

	M1. RR_{global}			M2. RR_{LOS}			M3. Q_{DCRP}			M4. LAM_{ARD}			M5. TT_{ARD}		
Predictors	B	β	*t*	B	β	*t*	B	β	*t*	B	β	*t*	B	β	*t*
Intercept	0.46	-0.10	**55.14*****	0.57	0.03	**29.27*****	0.02	-0.21	**7.83*****	0.02	-0.02	**8.93*****	0.11	-0.25	**6.90*****
Agreeableness "A" (A_A)	-0.00	-0.02	-0.17	-0.01	-0.09	-0.62	-0.00	-0.04	-0.30	-0.00	-0.12	-0.81	0.00	0.03	0.18
Agreeableness "B" (A_B)	-0.01	-0.09	-0.67	-0.01	-0.10	-0.73	-0.01	-0.23	-1.67	0.00	0.07	0.48	-0.00	-0.12	-0.82
T2. Self-disclosure	0.00	0.07	0.66	-0.02	-0.12	-1.31	0.00	0.14	0.79	0.00	0.10	0.63	0.05	0.42	**2.38***
T3. Argumentative	0.02	0.34	**3.23****	0.02	0.12	1.31	0.01	0.50	**2.81****	-0.00	-0.04	-0.23	0.05	0.39	**2.20***
A_A * A_B	-0.01	-0.09	-0.81	-0.02	-0.12	-1.01	-0.00	-0.12	-1.12	-0.00	-0.15	-1.32	-0.01	-0.10	-0.85
A_A * Task 2	-0.00	-0.01	-0.11	0.00	0.02	0.20	-0.00	-0.21	-1.10	0.00	0.32	1.85	0.02	0.17	0.90
A_A * Task 3	-0.01	-0.09	-0.77	-0.00	-0.02	-0.17	-0.00	-0.15	-0.80	0.00	0.42	**2.44***	0.01	0.12	0.65
A_B * Task 2	-0.00	-0.04	-0.36	-0.01	-0.08	-0.87	0.01	0.56	**3.06****	0.01	-0.07	-0.45	0.01	0.12	0.65
A_B * Task 3	-0.02	-0.26	**-2.37***	-0.03	-0.18	**-2.01***	0.01	0.26	1.42	-0.00	0.29	1.76	-0.03	-0.21	-1.15
A_A*A_B*Task 2	-0.00	-0.01	0.87	0.00	0.03	0.35	0.00	0.16	1.08	0.00	0.07	0.55	0.00	0.04	0.26
A_A*A_B*Task 3	-0.01	-0.14	-1.57	-0.01	-0.08	-1.12	0.00	0.16	1.06	0.00	0.36	**2.74****	-0.01	-0.04	-0.29
Random Effects															
ICC	0.70			0.79			0.13			0.29			0.16		
Marg. R^2/Cond. R^2	0.090/0.727			0.071/0.808			0.130/0.241			0.117/0.377			0.105/0.252		
AIC	-379.7			-176.4			-599.3			**-716.3**			-122.2		

*Note: B=unstandardized raw estimate; β=beta weights (standardized). * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p-values were BH corrected (Benjamini & Hochberg, 1995) FDR procedure. Task 1 (Introduction) is the baseline. Task 2 = Self-disclosure; Task 3 = Argumentative. A=Agreeableness. ICC = Intraclass Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered/scaled. RR_{global}= Recurrence Rate Global, RR_{LOS}= Percentage of Speech across the line of Synchrony (lag-zero), Q_{DCRP} = Quotient Diagonal Cross-Recurrence Profile (absolute), LAM_A= anisotropic Laminarity, TT_A= anisotropic Trapping Time, LAM_{ARD}= Relative difference of anisotropic Laminarity, TT_{ARD} = Relative difference of anisotropic Trapping Time. Definitions of each measure can be found in Table 1.*

Chapter 6

Relationship between Temperamental Dimensions and Infant Limb Movement Complexity and Dynamic Stability

Submitted as:

Arellano-Véliz, N. A., Laudańska, Z., Duda-Goławska, J., Cox, R. F. A., & Tomalski, P. Relationship between Temperamental Dimensions and Infant Limb Movement Complexity and Dynamic Stability. Preprint available at SSRN: https://ssrn.com/abstract=4891778 or http://dx.doi.org/10.2139/ssrn.4891778

Abstract

Dimensions of infant temperament describe behavioral responses to stimulation; however, motor systems undergo considerable changes throughout infancy, and they are also affected by caregivers' mental well-being. In this paper, we investigate temperamental associations with high-level measures of motor system organization at 6 and 12 months of age across three different social interaction tasks. To capture the effects of caregiver mental well-being, we also include maternal trait anxiety in the analysis. In a longitudinally studied sample of 83 (at 6 months) and 59 (at 12 months) infants, we measured their limb movements with wearable accelerometers during three tasks with their caregiver (book sharing, manipulative toys, and rattle-shaking). We used Multidimensional Recurrence Quantification Analysis (MdRQA) and extracted the variables of Entropy and Mean Line, which provide information about motor systems' complexity and stability, respectively. Using mixed-effects models, we evaluated the predictive effect of task and temperamental variables: Negative Affectivity (NEG), Positive Affectivity or Surgency (PAS), and Orienting and Regulatory Capacity (ORC). Our results suggest that Negative Affectivity predicted increased motor system Entropy and Mean Line at 6 months as well as longitudinally at 12 months. Temperamental variables measured at 12 months of age did not predict infants' motor systems' complexity and stability at the same time point. However, only at 12 months of age, Entropy and Mean Line were modulated by task. Finally, higher maternal anxiety (measured at 4 months of an infant's age) predicted decreased motor systems' Entropy and Mean Line at 12 months of age. Our results have implications for understanding the early developmental pathways of motor system organization and its relationship with temperament, as well as the influence of caregiver mental well-being on infant's motor development.

Keywords: infancy, accelerometry, limb movement, motor development, temperament, IBQ-R, Negative Affectivity, maternal anxiety, Multidimensional Recurrence Quantification Analysis

1. Introduction

Cognitive and motor development are fundamentally connected, and along with it, infants' bodies, environments, and experiences are linked to behavioral adaptability, rendering them crucial to the understanding of developmental outcomes later in life (Adolph & Hoch, 2020). Here, we propose to study temperament dimensions in infancy in relation to the development of motor system features, which allow for flexible adaptations to environmental constraints (Aßmann et al., 2007; Abney et al., 2014). The term "temperament" refers to stable individual differences in both emotional and behavioral reactivity observed during infancy (Tang et al., 2020). These individual characteristics (or traits) have a biological and genetic basis reflecting individual differences in reactivity and self-regulation (e.g., Rothbart & Derryberry, 1981). Temperament is particularly characterized by variation in responsiveness and self-regulation across emotional, motor, and attentional dimensions (Rothbart, 1981; Rothbart et al., 2004; Vonderlin et al., 2008). Reactivity refers to the responsiveness of emotional, activation, and arousal systems, while self-regulation encompasses processes such as approach, avoidance, and attention modulation. An infant's temperament develops from interactions between inheritance, maturation, and experience (e.g., Rothbart, 1981; Rothbart & Derryberry, 1981). Infant temperament is commonly understood as one of the earliest indicators of psychological differences in childhood (Sieber & Zmyj, 2022). It is thought to shape an individual's emotional and motor reactivity and to play a significant role in subsequent social interactions, social functioning (Calkins, 2012), and personality development over the lifespan (e.g., Tang et al., 2020; McCrae et al., 2020; Sieber & Zmyj, 2022).

Early in life, specifically the newborn and early infancy period, five primary temperament dimensions have been described: two dimensions related to negative reactivity (fearfulness/distress toward novelty and frustration/distress regarding limits), one dimension concerning positive affect (smiling and laughter), alongside distractibility/attention span (duration of orienting responses to new stimuli), and activity level (motor activity) (Rothbart et al., 1995). By the end of the first year, the child begins to exhibit effortful control and executive attention capabilities, allowing for more effective regulation and inhibition of responses. These developmental processes occur concurrently with the child's active planning skills and increasing adaptability to changing circumstances (Rothbart et al., 2004). Thus, this theoretical approach to temperament extends beyond the emotional realm by considering individual differences in reactivity and self-regulation, incorporating activity level, orienting, and executive attention into the temperament construct (Vonderlin et al., 2008).

Contemporary conceptualizations of temperament describe at least three distinct temperamental domains (Shiner et al., 2012): 1) Negative affectivity or negative emotionality (NEG); 2) Positive affectivity or surgency (PAS); 3) Effortful control or

Orienting and Regulatory Capacity (ORC) (Casalin et al., 2012). Negative affectivity refers to the tendency of infants to experience anger, fear, frustration, discomfort, and sadness (Shiner et al., 2012). Children with high Negative Affectivity can seem easily distressed, fearful, and shy; and they can exhibit negative facial expressions (like frowning) and demonstrate distress in behaviors like crying (Olino et al., 2011; Wittig & Rodriguez, 2019). Positive affectivity/surgency refers to the overall level of activity, impulsivity, positive anticipation, and sensation seeking in infants (Wittig & Rodriguez, 2019); and it is the developmental precursor of Extraversion. High Positive Affectivity/Surgency can be expressed in laughter, smiling, and increased motor activity (Putman et al., 2008). Orienting and regulatory capacity promote the development of effortful control (Putnam et al. 2008). In this sense, infants with increased Orienting and Regulatory Capacity are capable of self-soothing when they are distressed (Gartstein & Rothbart, 2003; Wittig & Rodriguez, 2019).

Biological approaches have been used to understand why and how people differ in temperament dimensions and later on in personality. A variety of methods has been applied, including quantitative genetics, biochemistry of brain neurotransmitters, resting-state brain oscillations, brain event-related potentials, and structural neuroimaging (see review in Reuter et al., 2022). The technological advances in the neuroscience field show evidence that brain structure, circuitry, and metabolism are indeed related to personality measured with parent-report or self-report questionnaires or laboratory paradigms (e.g., Marshall et al., 2009). However, the results obtained in different studies vary significantly, frequently supporting opposite views. However, this should not come as a surprise when one considers that living organisms are complex adaptive systems with many interdependent subsystems (Richardson et al., 2014). These organisms engage in continuous interactions with their material and social worlds (Thompson & Varela, 2001), and their neuroendocrine, neural, and physiological compositions can change dynamically and form a multilevel network of regulatory activities (e.g., Bashkatov & Garipova, 2022; Trofimova et al., 2016, 2018).

A similar approach is proposed within the dynamic systems perspective (Thelen & Smith, 1994). Within this perspective, motor actions are understood as the elements that are assembled for functional purposes in a flexible, task-specific manner, which is determined by the current environmental context, infant maturational status, and previous experience (Fogel & Thelen, 1987; Thelen & Smith, 1994). The infant's actions are emergent from the entire system of elements in a particular time and context - and are most probably affected by the child's reactivity and self-regulation patterns.

In developmental research, the child's motor activity level has been a frequently studied dimension of temperament, as it is associated with the patterning of gross and fine motor activity (e.g., Buss & Plomin, 1975; Schaffer, 1966; Thomas et al., 1963; see Rothbart & Derryberry, 1981 for a review). Sofologi et al. (2021) also showed that effortful control can have a positive effect on motor coordination, whereas Hammal and colleagues (2015) found that the velocity of infants' head movements varies across phases of the Still-Face paradigm, reflecting self-regulation. Furthermore, movement is considered a key modality through which temperament is expressed in infants (Planalp et al., 2017; Lev-Encab et al., 2022). However, to the best of our knowledge, the relationship between the child's temperament and their motor system complexity measured with nonlinear methods of data analysis has not been previously investigated. Thus, in this paper, we first use traditional parent-report questionnaire measures of infant temperament at 6 and 12 months of age as well as a questionnaire measure of maternal anxiety. Second, we measure the acceleration of spontaneous infant limb movements with wearable motion trackers during three different types of infant-parent play at 6 and 12 months of age (book-sharing, playing with manipulative toys, and rattle-shaking). Third, we use a nonlinear method of data analysis to determine the infant's motor system complexity and dynamic stability. Finally, we investigate the relationship between the child's temperament and their motor system complexity and dynamic stability concurrently at 6 and 12 months – and longitudinally between 6 and 12 months of age.

Approaches to temperament in developmental psychology emphasize the individual's developing capacity for control over self and environment, making it an integrative view of biological and behavioral aspects of temperament by operating with terms like reactivity and self-regulation (Derryberry & Tucker, 2015). Temperament must be considered an open system, which is influenced by ongoing interactions with the environment (Sofologi et al., 2021; Putnam et al., 2008). Early variations in the likelihood of experiencing positive or negative moods, becoming aroused in response to environmental transactions, or self-regulating after being upset are examples of temperamental factors in the interaction with the environment in which the infants are developing (Cervone & Pervin, 2019).

As part of the environment that plays a role in infants' development, caregivers are fundamental. In this regard, maternal anxiety has been linked to various developmental and psychological outcomes in infants (Glasheen et al., 2010; Field, 2018; del Hoyo-Bilbao & Orue, 2024). It predicted anxious-depressive symptomatology (Barker et al., 2011; O'Connor et al., 2002) and behavioral problems in children (Behrendt et al., 2020). Maternal anxiety is also associated with infants' temperament, particularly Negative Affectivity (NEG) (Spry et al., 2020). Maternal anxiety also relates to other temperament dimensions such as effortful control (ORC) and Positive Affectivity/Surgency (PAS). A longitudinal association was found between maternal anxiety in infancy and lower effortful control and higher surgency levels at 3 years of age (Behrendt et al., 2020). Similarly, various forms of maternal anxiety during prenatal and postnatal periods were individually linked to perceived difficulties in infant temperament. In particular, chronically high maternal anxiety, whether pregnancy-specific or general, predicted the highest perceived infant activity level and Negative Affectivity at 6 months postpartum

(Henrichs et al., 2009). In addition, a recent study showed that the relationship between maternal anxiety and infant Negative Affectivity was explained through the mediating roles of parenting self-regulation and the child's emotional awareness (del Hoyo-Bilbao & Orue, 2024). Similarly, the connection between maternal anxiety and infant effortful control was mediated by the caregiver's compassion and attentive listening to the child (del Hoyo-Bilbao & Orue, 2024). In this sense, maternal anxiety after childbirth represents a critical time for the development of infant temperament, cognitive and motor development (Keim et al., 2011). Recent research suggests the existence of critical time points in which maternal mental health predicts cascading influences on child development outcomes such as temperament, across the first 6 months of life (Rigato et al., 2020). Similarly, high levels of maternal stress were associated with excessive crying, infant fussiness at 6 months old, and disruptive sleep patterns at 6 and 12 months of age (Bradley et al., 2023).

Consequently, the first year of life emerges as a sensitive period for infants' development, wherein maternal anxiety and stress can have a significant long-term impact (Berhrent et al., 2020). Therefore, given the link between maternal mental health and its effects on infants' developmental trajectories, identifying factors shaping this relationship and understanding other developmental consequences becomes crucial for enhancing caregiver-child interactions, interventions, and infants' mental health (Henrichs et al., 2009; del Hoyo-Bilbao & Orue, 2024).

1.1. The present study

We aimed to investigate whether the dynamic organization of infants' motor behaviors is related to temperament and maternal anxiety at two time points across infancy: 6 and 12 months of age. During the second half of the first year of life, infants' motor system undergoes dramatic changes, resulting in the acquisition of novel body postures (sitting, crawling, pulling to stand), which is often accompanied by the refinement of their fine motor skills. Specifically, we aimed to investigate infants' motor systems' complexity and dynamic stability, which were operationalized as the Entropy and Mean Line measures of Multidimensional Recurrence Quantification Analysis (MdRQA) calculated from the time series of accelerometric limb movement data. Multidimensional Recurrence Quantification Analysis (MdRQA, Wallot, et al., 2016) is a nonlinear analysis technique employed to capture temporal patterns in multidimensional time series. It is a multivariate extension of Recurrence Quantification Analysis (RQA, e.g., Marwan et al., 2007). Detailed information describing the method, measures, and interpretation can be found in the Method section. This method has been previously used to test the effect of task demands on infant limb movement coordination (Laudańska et al., 2022a).

To assess the relationship between temperamental variables on infants' motor systems' complexity and dynamic stability, infants' limb movement patterns were measured across three types of infant-parent games (book-sharing, rattle-shaking, and play with manipulative toys) typically associated with different types of coordinated responses. The temperament dimensions considered in this study are Negative Affectivity (NEG), Positive Affectivity/Surgency (PAS), and Orienting and Regulatory Capacity (ORC) as measured by the widely used Infant Behavior Questionnaire-Revised (IBQ-R, Rothbart, 1981).

We expected task-related differences in limb movement coordination to emerge at a later age (12 months), as shown by Laudańska et al., 2022a). We also expected more coordinated motor actions (e.g., stability) while exploring toys with interesting tactile structures, more rhythmic and stable patterns during rattle-shaking, and less defined motor coordination patterns during book-sharing, which involves more vocal than motor actions. The potential lack of clear motor coordination patterns in book-sharing could lead to a lack of clear relations between limb movement complexity and stability.

Moreover, considering the associations between maternal mental well-being, such as maternal anxiety, and child development during the first year of life (Miller et al., 2021), we include the caregivers' anxiety levels in final exploratory analyses.

1.1.1. Hypotheses

Table 1. Summary of predictions for the effect of temperament on infant motor organization by time point and task

Expectation	Description	Task effects	Longitudinal effects
H1	Lower values of Negative Affectivity would be related to higher complexity (Entropy) at concurrent time points (6 and 12 months).[1]	H1a: Association of Negative Affectivity and motor system complexity would be greater for rattle-shaking and playing with manipulative toys than for book-sharing due to more vocal than motor actions.	H1b: Lower values of Negative Affectivity at 6 months predict higher complexity (Entropy) at 12 months.
H2	Lower values of Negative Affectivity would be related to higher dynamic stability (Mean Line) at concurrent time points (6 and 12 months).[1]	H2a: Association of Negative Affectivity and motor system's dynamic stability would be greater for rattle-shaking and play with manipulative toys than for book-sharing due to more vocal than motor actions.	H2b: Lower values of Negative Affectivity at 6 months predict higher dynamic stability (Mean Line) at 12 months.
H3	Lower Positive Affectivity/Surgency would be related to lower complexity (Entropy) at concurrent time points (6 and 12 months).[2,3]	H3a: Association of Positive Affectivity/Surgency and motor system's complexity relation would be greater for rattle-shaking and playing with manipulative toys than for book-sharing due to more vocal than motor actions.	H3b. Lower Positive Affectivity/Surgency at 6 months predicts lower complexity (Entropy) at 12 months.
H4	Higher Orienting/ Regulatory Capacity would be related to higher dynamic stability (Mean Line).	H4a: Association of Orienting/ Regulatory Capacity and motor system's dynamic stability relation will be greater for rattle-shaking and playing with manipulative toys than for book-sharing due to more vocal than motor actions.	H4b: Higher Orienting/ Regulatory Capacity at 6 months predicts higher dynamic stability (Mean Line) at 12 months.
H5	Exploratory analyses of the relationship between maternal anxiety and infant motor system complexity and stability at 6 and 12 months.		

Note: 1 Arellano-Véliz et al (2024b); 2 Adolph & Hoch, 2019; 3 Arellano-Véliz et al (2024a). These hypotheses were preregistered and can be accessed at https://doi.org/10.17605/OSF.IO/HSM8Z

2. Method

2.1. Participants

Participants were 104 infant-parent dyads who were invited to the lab when infants were around 4 (T1), 6 (T2), 9 (T3), and 12 (T4) months old. 83 dyads participated in a minimum of three visits, out of them, 48 dyads contributed data at all 4-time points (missed visits are mostly due to COVID-19-related restrictions as data collection was conducted between the years 2020 and 2023). Therefore, 20 dyads contributed data at T2, T3 and T4, 7 at T1, T3, T4, and 8 at T1, T3 and T4.

For the present study, we focused on T2 (6 months old) and T4 (12 months old), for which a sample of 83 and 59 infants was available, respectively. Participants were from predominantly middle-class families living in a city with >1.7 million inhabitants. The majority (90%) of the caregivers had completed higher education: 3 held a Ph.D. degree, 81 held a master's degree, 10 held a bachelor's, and 4 completed high school (6 missing data). For their participation, infants received a diploma and a small gift (a baby book). The study received clearance from the Research Ethics Committee at the [blinded for peer-review].

2.2. Assessment of temperament

The infant's temperament was measured using two versions of the Polish adaptation of the Infant Behavior Questionnaire-Revised (IBQ-R, Rothbart, 1981). When infants were at the age of 6 months (T2), the IBQ-R Very Short Form was used (Putnam et al., 2014), and when they were 12 months old (T4), the IBQ-R Full version was used (Gartstein & Rothbart, 2003, Polish adaptation by Dragan, Kmita, and Fronczyk, 2011). Three dimensions were calculated: Negative Affectivity (NEG), Positive Affectivity/Surgency (PAS), and Orienting/Regulatory Capacity (ORC). In the IBQ-R Very Short Form, the estimated internal consistency (Cronbach's alpha) for Negative Affectivity (NEG), Positive Affectivity (PAS), and Orienting/Regulatory Capacity ranged from .71 to .81 (Putnam et al., 2014). For the Polish adaptation of the IBQ-R full version, the internal consistency was satisfactory, ranging in the scales from .71 to .90 (Dragan et al., 2011). Both versions are composed of 14 scales: high-intensity pleasure, approach, soothability, smiling and laughter, cuddliness, vocal reactivity, distress of limitations, sadness, falling reactivity, activity, duration of orienting, perceptual sensitivity, low-intensity pleasure, and fear (Putnam et al., 2014; Dragan et al., 2011).

2.3. Assessment of maternal anxiety

Maternal anxiety may affect the quality of interactions with the infant (e.g., Kaitz et al., 2010). Furthermore, elevated anxiety symptoms appear to have a distinct association with maternal reports of child development and temperament (Miller et al., 2021). Thus, we measured maternal trait anxiety using the Polish version of the State-Trait Anxiety Inventory (STAI; Spielberger et al., 1983; Polish adaptation by Spielberger et al., 1987). Maternal trait anxiety was measured when infants were 4 months of age.

2.4. Equipment

Infants' and caregivers' movements were recorded at 60 Hz using wearable motion trackers (MTw Awinda, Xsens Technologies B.V.), an Awinda station receiver. (Xsens Technologies B.V.) and MT Manager Software (Xsens Technologies B.V.). Overall, 12 sensors were used (on the infant's arms, legs, head, and torso; and on the caregiver's arms, head, and torso), but in this paper, we report data only from four sensors placed on the infant's arms and legs.

2.5. Procedure

Interactions were recorded in an infant-friendly laboratory room on a carpeted play area. Upon the family's arrival, an experimenter explained the study protocol and obtained parental consent. Once the infant was familiarized with the laboratory, the wearable motion trackers attached to the elastic bands were put on the infant's and caregiver's bodies. Then, a set of parent-child interaction tasks with different sets of age-appropriate toys took place. The sets for infants aged 6 months were slightly different from those for infants aged 12 months to maintain their interest in a given task as well as to adjust the size and weight of objects to infants' motor skills (see Figure 1). There were 6-7 different tasks during each meeting, but here we report data comparing three of them - book-sharing, playing with manipulative toys, and rattle-shaking.

Figure 1. Pictures of the set of toys used on each task

Note: The sets of toys used for each play. The top row indicates toys used during the visit at 6 months, and the bottom row indicates toys used at 12 months.

2.5.1. Task 1: Book-sharing

In a book-sharing task (also referred to as "books"), the dyads were provided with several baby books. At 6 months, there were three small picture books: one with nursery rhymes, one with big pictures of animals and people, and one with pictures and onomatopoeic words. At 12 months, infants and parents were given one bigger book with pictures and onomatopoeic words and one smaller book with animal pictures, nursery rhymes about animals and tactile elements.

2.5.2. Task 2: Manipulative toys

In a manipulative toys task (also referred to as "manipulative"), infants and parents were given a set of toys that varied in tactile structure and provided multimodal feedback (sounds, movements). Two toys were the same at all time points: a sensory pop-it toy and a gliding, rolling and rattling sensory toy with tactile silicone elements. In addition, at 6 months, the set consisted of a wooden wiggly worm, a sensory toy with different tactile fabric and silicone elements, and a grasping ball with finger holes and rattling beads, whereas at 12 months: a spinning toy with small balls inside, a sensory-exploration toy with elements with different textures that can be pushed, spun or clicked and make different sounds.

2.5.3. Task 3: Rattle-shaking

In a rattle-shaking task (also referred to as "rattles"), which lasted approx. In 5 minutes, the dyads were given two maracas rattles and two rattles of different types (the barbell rattles for younger infants and teddy bear rattles for older ones).

2.6. Data Pre-processing

IMU data from sensors placed on both wrists and ankles of an infant were processed in Matlab (Mathworks, Inc, Natick, USA) using in-house scripts. The acceleration signals in three movement directions were selected for further analysis. The IMU tracking system, which measures the orientation of the user, operates wirelessly through a WiFi connection. However, occasional issues with wireless connectivity led to missing values in the IMU data. These missing values were primarily caused by internal features of the IMU sensors and automatic adjustments in the sampling rate from 60 Hz to 40 Hz. To ensure the comparability of time series data, missing values in the packages were interpolated using Matlab functions such as fillmissing ('linear') and interp1 with 'spline' parameter. On average, there were 3.15% (SD=10.21) missing values. When a lower sampling rate was detected in .mtb files, the signal was resampled using the resample Matlab function. No filtering was applied to preserve all characteristics of IMU signals. Additionally, to investigate the acceleration information, the magnitude of acceleration for each three-dimensional acceleration data point was computed and collapsed into one-dimensional time series:

$$\mathrm{Acc} = \sqrt{}\mathrm{x(t)^\wedge 2\ + y(t)^\wedge 2 + z(t)^\wedge 2} \qquad (1)$$

where x,y,z,$\in R^{1xN}$, and the variables x(t),y(t),z(t), represent the accelerations along the three spatial dimensions over time. These processing steps were crucial to ensure the quality and reliability of the IMU data for further Multidimensional Recurrence Quantification Analysis and interpretation in studying infant movement patterns.

2.7. Time series analysis: Multidimensional Recurrence Quantification Analysis (MdRQA)

Recurrence methods such as Recurrence Quantification Analysis (RQA), which involves the study of recurrent patterns in a system's behavior, have been widely used to capture the dynamic organization of complex dynamic systems (Marwan et al., 2007; Anderson et al., 2013; Main et al., 2016; Jenkins et al., 2020). The proper assessment of a system's dynamics involves the consideration of its multidimensional nature (Wallot & Leonardi, 2018). This consideration is relevant, for example, in the assessment of different physiological, behavioral, or emotional processes, as it is generally accepted that one single modality of measurement (heart rate, movement) does not provide complete accuracy regarding the underlying processes and mechanisms of such complex systems (Wallot & Leonardi, 2018).

Multidimensional Recurrence Quantification Analysis (MdRQA) is a method that facilitates the analysis of multiple layers of data over time (Wallot & Leonardi, 2018). MdRQA, like other recurrence analyses, measures how our variables of interest repeat their values or trajectories over time (Wallot et al., 2016). However, its particularity relies on its multidimensional approach, being able to analyze multiple layers of data (time series) within individuals (multivariate, multidimensional system) or joint dynamics of a group of variables over time (Wallot et al., 2016). MdRQA examines a singular system observed through two or more measured variables, and consequently, it assesses the auto-recurrence characteristics of a multidimensional or multivariate system (Hall et al., 2023; Wallot & Leonardi, 2018). This technique extends the study of systems' trajectories to multiple dimensions and allows for the investigation of interactions between variables or levels of analysis.

MdRQA, like other recurrence-based methods, involves reconstructing the phase space of a system using time-delayed embedding. In this process, multiple recorded time series are integrated into a single phase space, with each time series contributing one or more dimensions to the reconstruction (Wallot & Leonardi, 2018). By doing so, MdRQA enables the quantification of dynamics in high-dimensional signals, considering the phase space of multiple time series of a system (or systems) as the starting point (Wallot et al., 2016).

The logic of estimating the parameters of delay and embedding dimension is the same as is employed in RQA (see Wallot et al., 2016, for a detailed explanation). These parameters dictate how the phase space is reconstructed and influence the analysis outcomes (Wallot et al., 2016). In this study, the delay was set to 1, and the embedding dimension to 10 (similar to Laudańska et al., 2022a). A 'match' or recurrence in this context represents the recurrence of a state within the multidimensional phase space constructed from infants' movements. Unlike categorical data, where a 'match' might directly correspond to observable behavior, here it symbolizes a return to a previous dynamic state within an abstract mathematical model (Wallot et al., 2016). This recurrence reflects the complex, non-linear nature of the self-organizing patterns that MdRQA is designed to capture. These patterns are not repetitions of specific, discrete behaviors but rather indicate the broader, underlying dynamics that govern the evolution of the motor system over time. By embedding the time series into multiple dimensions, MdRQA uncovers these relationships, revealing the temporal coordination and organization in the system that might not be apparent in observable movements.

We extracted the measures Entropy and Mean Line, which provide information about the systems' dynamic organization, as explained in Table 2.

Table 2. MdRQA measures' definition and interpretation

Measure	Definition	Interpretation
Entropy (ENT)	Shannon Entropy calculated from the distribution of diagonal line lengths in the recurrence plot. It captures repeating movement patterns.[1]	Entropy is used to quantify the diversity or complexity of the deterministic patterns of the multidimensional system.[1,2] It can be interpreted as the degrees of freedom of the synergies in the limbs' movements.[2] Higher Entropy values can indicate both, greater complexity and less predictability in the system's behavior.[3]
Mean Line (ML)	Average length of diagonal lines in the recurrence plot. It indicates the average length of patterns of recurrences.[1]	Mean Line measures the average duration of deterministic patterns in the multidimensional time series data.[2] Mean Line can be interpreted as a measure of the stability of the multidimensional motor system. Larger values of the Mean Line (longer average durations) can be interpreted as higher stability, whereas lower values are interpreted as low stability of the system's dynamics.[1,2]

Note: 1 Wallot & Leonardi (2018); 2Laudańska et al. (2022); 3De Jonge-Hoekstra et al. (2020).

2.7. Statistical Analysis

To estimate the association between the temperament variables (NEG, PAS, ORC) and our MdRQA variables (Entropy and Mean Line), Maximum Likelihood (ML) linear mixed-effect models were performed using the 'lme4' R package (Bates et al., 2015). The models have a hierarchical two-level structure, where the participant scores in each task are nested within the individual structure. Level 1 corresponded to "task," the individual observations of the outcome variable (Entropy; Mean Line) by each task (book-sharing, rattle-shaking, playing with manipulative toys). Level 2 corresponded to "individuals" (infants).

Different sets of models were conducted at 6 months, 12 months, and subsequently, a set of models predicting motor complexity at 12 months from temperament dimensions at 6 months. The dependent variables of each model were Entropy and Mean Line, respectively, and the predictors were the temperament variables and the type of task additively. We run separate models in sequential steps for each temperament variable to gain insight into the unique contribution of each predictor (NEG, PAS, ORC) in the outcome variable Entropy.[1] In the final step, a comprehensive full model was performed including all temperament variables (additively) in interaction with the task.

Our models have three temperament fixed-effect predictors (NEG, PAS, ORC) that are assumed to have a relatively consistent relationship with the outcome variable across the population. In addition, we have a categorical variable (task) that is also included as a fixed-effect predictor, which has three levels (tasks: book-sharing, manipulative toys, rattle-shaking), where the task "book-sharing" was considered the baseline. This variable allows us to investigate whether the relationship between the temperament variables of the babies and the outcome variables varies depending on the specific task. The random effect was specified as "(1|Participant ID)", which assumes that there is individual variability in the intercept of the relationship between the predictors and outcomes across different participants (for information related to the package, consult 'lme4' R package, Bates et al., 2015). This random effect accounts for the fact that different participants may have different baselines of the outcome variable (MdRQA or motor system variables), even after accounting for the fixed-effect predictors (temperament). The combination of both fixed and random effects contributes to the generalizability of the results.

As an exploratory set of analyses, the effect of maternal anxiety (measured at 4 months) was assessed through mixed effects models. In this case, the variable of maternal trait anxiety (STAI) was considered as a predictor together with the task interactively, and the response variables were Entropy and Mean Line, as+ in the previous models. Subsequently, the temperament variables were incorporated into separate models and a full model. This procedure was conducted with the MdRQA variables Entropy and Mean Linea at 6 and 12 months, indicating concurrent and longitudinal effects, respectively.[2]

The predictor variables (temperament scores) were centered to ensure an adequate convergence of the models. We report both estimates and standardized beta weights (β) and model estimates. This is under the reasoning that beta weights can be interpreted as effect sizes (e.g., Paxton & Dale, 2013). For linear mixed effects, all continuous predictors were standardized before being incorporated into the models to obtain beta weights. Temperament variables were centered by subtracting the mean. All statistical analyses were conducted using R (R core team, 2022), RStudio (RStudio Team, 2023), lme4 package (Bates et al., 2015) and visualized using ggplot2 (Wickham, 2016).

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*1 This is the structure of the models: Entropy ~ (NEG) * task + (1|Participant ID); Entropy ~ PAS + task + (1|Participant ID); Entropy ~ ORC + task + (1|Participant ID); Mean Line ~ NEG + task + (1|Participant ID); Mean Line ~ PAS + task + (1|Participant ID); Mean Line ~ ORC + task + (1|Participant ID).*

*2 Example of the model incorporating maternal anxiety and task: Entropy ~ STAI * task + (1|Participant ID)*

3. Results

3.1. IBQ-R Descriptives at 6 months and 12 months of age

The descriptive statistics for temperament variables, as assessed by the IBQ-R, offer information about the dimensions of infants' temperament during the first year of life (see Table 3). At 6 months, infants exhibited an average score of 3.65 (SD = 0.93) on Negative Emotionality (NEG). Positive Affectivity/Surgency (PAS) exhibited a mean score of 4.66 (SD = 0.70). And Orienting/Regulatory Capacity (ORC), showed a mean score of 4.80 (SD = 0.59). By 12 months, the mean score for NEG was 3.94 (SD = 0.41). PAS exhibited a mean score of 4.95 (SD = 0.42). ORC exhibited a mean score of 4.50 (SD = 0.48) (see Table 3).

Table 3. Descriptive statistics for infants' temperament variables (IBQ-R)

Variable	M	SD	Range
Negative Affectivity, NEG (6 months)	3.65	0.93	[1.58, 5.64]
Positive Affectivity/Surgency, PAS (6 months)	4.66	0.70	[3, 6.15]
Orienting/Regulatory Capacity, ORC (6 months)	4.80	0.59	[3, 6.75]
Negative Affectivity, NEG (12 months)	3.94	0.41	[3.06, 4.76]
Positive Affectivity/Surgency, PAS (12 months)	4.95	0.42	[3.99, 5.92]
Orienting/Regulatory Capacity, ORC (12 months)	4.50	0.48	[3.60, 6.02]

Note: N6 months = 83 participants. N12 months = 59 participants. M = mean, SD = standard deviation.

3.2. Correlations between IBQ-R scores at 6 and 12 months

Temperament variables measured at 6 and 12 months of age were significantly correlated: Negative Affectivity (NEG) ($r = 0.59$, $p < .001$), Positive Affectivity/Surgency (PAS) ($r = 0.56$, $p < .001$), and Orienting and Regulatory Capacity (ORC) ($r = 0.57$, $p < .001$) (see Table 4).

Table 4. Correlations between IBQ-R scores at 6 and 12 months

Variable	NEG (6 months)	PAS (6 months)	ORC (6 months)	NEG (12 months)	PAS (12 months)	ORC (12 months)
NEG (6 months)	-					
PAS (6 months)	0.20	-				
ORC (6 months)	-0.06	**0.31***	-			
NEG (12 months)	**0.59****	0.18	-0.11	-		
PAS (12 months)	**0.42****	**0.56****	**0.35***	**0.38****	-	
ORC (12 months)	0.14	0.20	**0.57****	0.05	**0.39***	-

*Note: Bold text indicates statistically significant correlations; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/ Regulatory Capacity. The correlation table displays the correlation between temperament variables at 6 and 12 months of age.*

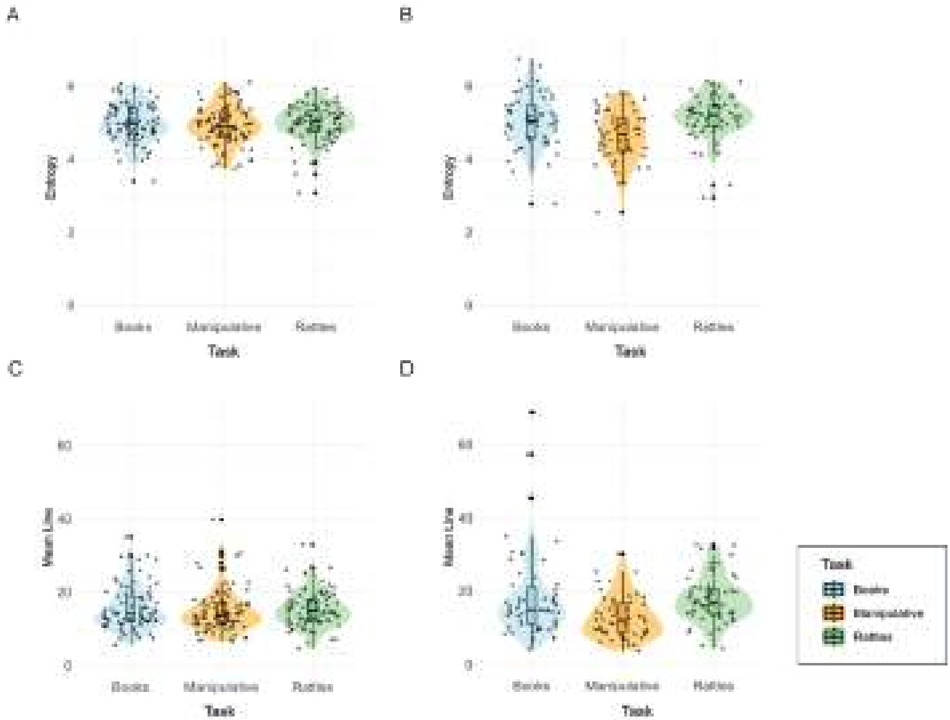
3.3. MdRQA measures of complexity and dynamic stability of limb movements at 6 and 12 months of age

3.3.1. Descriptives of MdRQA

The descriptive results indicate that at 6 months, the mean Entropy scores were slightly lower in task 2, manipulative toys ($M = 4.91$, $SD = 0.52$), and equal in task 1, book-sharing ($M = 4.99$, $SD = 0.53$) and task 3, rattle-shaking ($M = 4.99$, $SD = 0.50$). Regarding stability, at 6 months, the Mean Line scores were lower in task 2, manipulative toys ($M = 14.98$, $SD = 6.04$), and higher in task 3, rattle-shaking ($M = 15.41$, $SD = 4.93$), and task 1, book-sharing ($M = 15.7$, $SD = 6.05$) (see Figure 2 and Table 5).

At 12 months, the mean Entropy scores were lower in task 2, manipulative toys (M = 4.63, SD = 0.71), followed by task 1, book-sharing (M = 5.05, SD = 0.73), and task 3 (rattle-shaking, M = 5.15, SD = 0.60). At 12 months, the task that showed the lowest stability was manipulative toys (M = 12.93, SD = 5.84), followed by rattle-shaking (M = 17.79, SD = 6.40), and book-sharing (M = 18.53, SD = 12) with the highest stability or Mean Line values (see Figure 2 and Table 5).

Figure 2. Distribution of Entropy and Mean Line at 6 and 12 months by task



Note: Violin plots display the distribution of the MdRQA variables at 6 and 12 months across the three different tasks: Entropy 6 months (panel A) and 12 months (panel B) and Mean Line at 6 months (panel C) and 12 months (panel D). Task 1, book-sharing is represented in light blue. Task 2, manipulative toys is represented in orange. Task 3, rattles is represented in green. Books = Book-sharing, Manipulative = Manipulative Toys, Rattles = Rattle-shaking.

Table 5. Descriptive statistics for infants' motor system dynamic complexity (Entropy) and dynamic stability (Mean Line) per task and time-point.

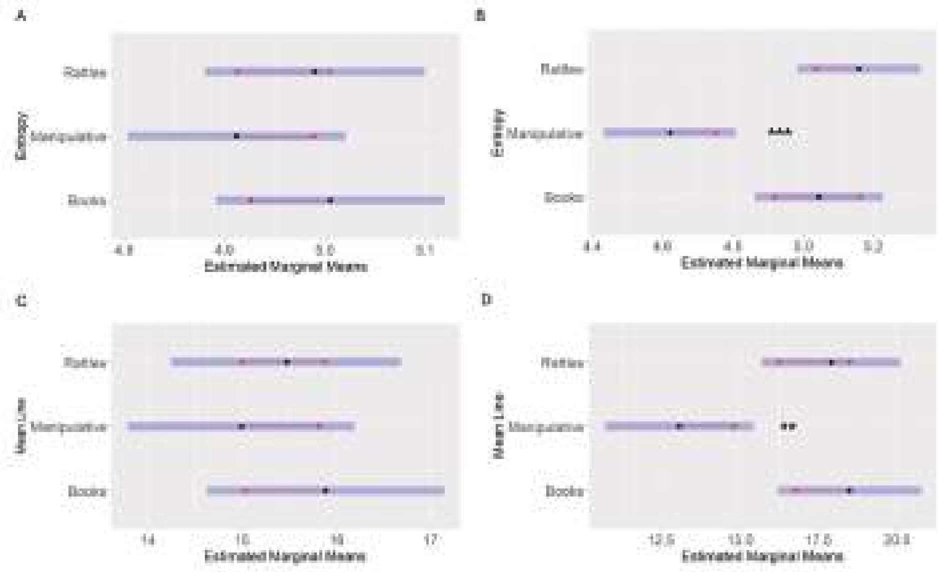
	Task 1. Book-sharing			Task 2. Manipulative toys			Task 3. Rattle-shaking		
Variable	**M**	**SD**	**Range**	**M**	**SD**	**Range**	**M**	**SD**	**Range**
Entropy (6 months)	4.99	0.53	3.40, 6.06	4.91	0.52	3.73, 6.11	4.99	0.50	3.08, 5.92
Mean Line (6 months)	15.7	6.05	5.60, 35.18	14.98	6.04	6.54, 39.89	15.41	4.93	4.63, 33.11
Entropy (12 months)	5.05	0.73	2.77, 6.74	4.63	0.71	2.55, 5.82	5.15	0.60	2.94, 6.14
Mean Line (12 months)	18.53	12	4.04, 68.88	12.93	5.84	3.68, 3.25	17.79	6.40	4.36, 32.80

Note: $N_{6\ months}$ = 83 participants. $N_{12\ months}$ = 59 participants. M = mean, SD = standard deviation.

3.4. Predicting MdRQA from task and temperament at 6 and 12 months of age

As detailed in the method section, linear mixed-effects models were employed to investigate the effects of task and temperament variables on infants' motor system dynamic complexity (Entropy) and dynamic stability (Mean Line). The models incorporated variations in tasks, with "Manipulative" designated as task 2 and "Rattle-shaking" as task 3, while task 1 (Book-sharing) served as the baseline (See Figure 3 for task effects on Entropy and Mean Line at 6 and 12 months).

Figure 3. Predicted effects of task on Entropy and Mean Line at 6 and 12 months



*Note: Signif. codes: 0 '***' .001 '**' .01 '*' .05 '.' .1 ' ' 1*

Predicted effects of different tasks on Entropy at 6 months (panel A) and 12 months of age (panel B), with the estimated values of Entropy of task 2 (Manipulative) < task 1 (Books) ($p < .001$). Predicted effects of different tasks on Mean Line at 6 months (panel C) and at 12 months of age (panel D), with the estimated values of the Mean Line of task 2 (Manipulative) < task 1 (Books) ($p < .01$). Task 1 (Books) was the baseline. Books = task 1, Manipulative = task 2, Rattles = task 3. Books = Book-sharing, Manipulative = Manipulative Toys, Rattles = Rattle-shaking. The central points or markers represent the adjusted means of the response variable for different levels of the predictor variables, accounting for the effects of other variables in the model. The blue bars are confidence intervals for the Estimated Marginal Means, and the red arrows indicate comparisons between the means of the tasks with the baseline task (Books).

3.4.1. Predicting motor system complexity (Entropy) and stability (Mean Line) concurrently at 6 months

3.4.1.1. Entropy

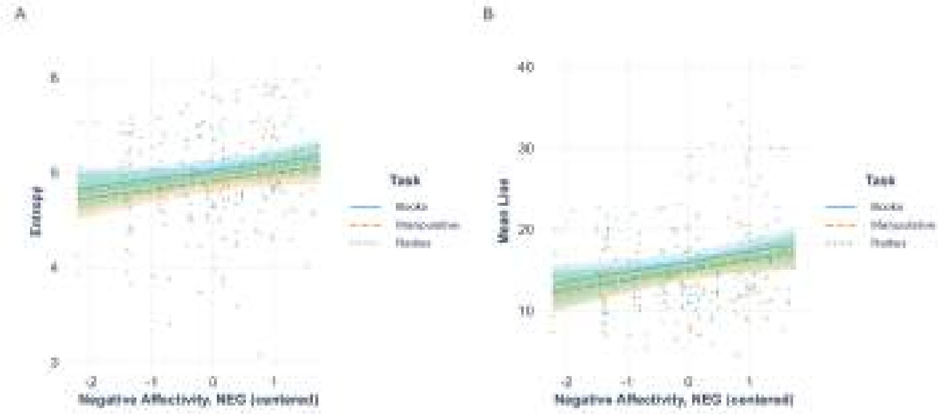
To analyze the effects of task and temperament variables (Negative Affectivity, NEG, Positive Affectivity/Surgency, PAS, and Orienting and Regulatory Capacity, ORC) on Entropy – infants' motor system complexity – at 6 months of age (concurrently), we employed a sequential modeling approach. First, we examined the influence of the task alone on Entropy, employing a model with the task as the sole predictor. The mixed-effects models included task variations, with "Manipulative" as task 2, and "Rattle-shaking" as task 3, and the baseline task "Book-sharing" was denoted as task 1. Subsequently, we individually modeled the effects of each temperament variable interacting with the task (see Table 6). This step allowed us to assess how each temperament trait modulated the relationship between the task and infant motor system complexity. Finally, we constructed a comprehensive full model incorporating additively all temperament variables in interaction with the task.

The intercepts in all models were found to be statistically significant ($p < .001$). The results of the analysis are presented in Table 6. In the first model, including only the task as a predictor of Entropy at 6 months (estimate = 5.01, SE = 0.06, $\beta = .08$, $p < .001$), there were no significant differences observed across tasks (see Model 1 in Table 6 and Figure 3A). In the next step (model 2), the estimate for NEG revealed a significant positive association with Entropy ($\beta = .17$, $p < .05$), which indicates that as NEG at 6 months was higher, the value of Entropy was predicted to increase as well (contrary to H1) (see Figure 4A). The marginal and conditional R2 values suggest that the fixed and random effects explain a substantial proportion of variability in Entropy (around 28.7%). There were no significant additive effects of task and NEG, therefore, H1a was not supported. There were no significant effects of PAS or ORC at 6 months on Entropy, therefore, H3 was not supported.

3.4.1.2. Mean Line

Subsequently, we modeled the effects of task and each temperament variable (NEG, PAS, ORC) on Mean Line – infants' motor dynamic stability – at 6 months. The same sequential modeling approach was employed. First, only the task was included, in the subsequent models each temperament variable was included separately, and finally, a comprehensive full model was performed including all temperament variables in interaction with the task. Similarly, no significant task effects were found (estimate = 15.88, SE = 0.64, $\beta = .07$, $p < .001$) (see Model 1 in Table 7 and Figure 3C). The estimate for NEG in models 2 and 5 (full model) revealed a significant positive effect ($\beta = .21$, $p < .01$; and $\beta = .21$, $p < .05$, respectively) (see Table 7). This suggests that as Negative Affectivity increased, the values of the motor system dynamic stability (Mean Line) were also expected to increase (contrary to H2) (See Figure 4B). No task effects were observed at 6 months in these models, therefore, H2a was not supported. The marginal and conditional R2 values for models 2 and 5 suggest that the fixed and random effects explain a substantial proportion of variability in Entropy (around 34%). No significant effects were found for PAS and ORC at 6 months, therefore, H3 and H4 were not supported in our sample.

Figure 4. Predicted effects of Negative Affectivity (NEG) on Entropy and Mean Line at 6 months



Note: NEG= Negative Affectivity. Panel A exhibits the effects of Negative Affectivity on Entropy and task at 6 months of age. In this case, only the effect of Negative Affectivity (NEG) was statistically significant (p < .05), and the effect of task was not significant (p > .05). Panel B exhibits the effects of Negative Affectivity on Mean Line (stability) and the task at 6 months of age. Only the effect of Negative Affectivity (NEG) was statistically significant (p < .05), whereas the effect of task was not significant (p > .05). NEG was centered and it represents the standardized scores of the original raw scores. Each unit in the x-axis corresponds to units of standard deviations from the centered mean of '0'. Books = Book-sharing, Manipulative = Manipulative Toys, Rattles = Rattle-shaking.

3.4.2. Predicting motor system complexity (Entropy) and stability (Mean Line) concurrently at 12 months

3.4.2.1. Entropy

We conducted the same sequential procedure to model task effects and each temperament variable (NEG, PAS, ORC) on Entropy – infants' motor complexity – at 12 months (concurrently). First, only the task was included as a predictor, in the subsequent models each temperament variable was included separately, and finally, a comprehensive full model included all temperament variables and task. The mixed-effects model included task variations, with "Manipulative" as task 2, and "Rattle-shaking" as task 3, and the baseline task "Book-sharing" was denoted as task 1. The intercepts in all models were found to be statistically significant ($p < .001$, see Table 8).

In the model including only task effects on Entropy, the intercept, estimated at 5.04, signifies the baseline Entropy level when infants are engaged in the reference task (task 1: book-sharing), this baseline level of Entropy was found to be statistically significant (SE = 0.09, β = .12, $p < .001$) (see Model 1, Table 8, and Figure 3B). The effect of the manipulative toys task (task 2) revealed a negative association with Entropy (estimate = -0.42, SE = 0.11, β = -.59, $p < .001$), indicating that when infants were engaged in the manipulative toys task, Entropy decreased compared to the baseline task (book-sharing). The effect of task 3 (rattle-shaking) was not statistically significant (β = .16, $p > .05$), indicating no significant difference in Entropy compared to the baseline task (book-sharing). The marginal R2 (0.102) and conditional R2 (0.345) values indicate that the fixed effects explain approximately 10.2% of the variability in Entropy, while both fixed and random effects combined explain about 34.5%.

When examining the impact of temperament variables (NEG, PAS, ORC) on Entropy, models were constructed with individual temperament variables, and a full model encompassing all temperament variables, and their interactions with specific tasks (see Table 8). In the models including each temperament variable individually (Models 2, 3, and 4, Table 8), only the fixed effect of the "Manipulative task" (task 2) was a significant predictor of Entropy in all models (all $p < .01$). The full model (Model 5) demonstrated that the fixed effect of the task was the only significant predictor of Entropy in infants at 12 months (β = -.55, $p < .01$). This suggests that the task differentiation effect on Entropy was predominantly relevant at 12 months. Temperament variables were not statistically significant in these models.

3.4.2.2. Mean Line

Subsequently, when examining the impact of task and temperament (NEG, PAS, ORC) on Mean Line (infants' motor dynamic stability), we followed the same sequential procedure mentioned before. First, the task was included as a predictor, and in the next steps, each temperament variable was included, to conclude with a comprehensive full model including all temperament variables and the task.

When modeling the effects of the task on the Mean Line at 12 months, the intercept of 18.48 (SE = 0.15, β = .22, $p < .001$) signifies the baseline Mean Line when infants are engaged in the reference task (task 1: book-sharing) (see Model 1, Table 9, and Figure 3D). The significant negative effect of task 2 (estimate = -5.41, SE = 1.52, β = -.61, $p < .01$) suggests that when infants are engaged in the manipulative toys task, their motor dynamic stability is lower compared to the baseline task 1. The effect of task 3 (Rattle-shaking) was not statistically significant (β = -.07, $p > .05$), indicating no significant difference in the Mean Line compared to the baseline task 1. The marginal R^2 (.073) and conditional R^2 (.226) values suggest that the fixed effects explain approximately 7.3% of variability in the Mean Line, while both fixed and random effects combined explain about 22.6%.

The task differentiation results at 12 months are congruent with the results previously presented by Laudańska et al. (2022a). However, both tasks, book-sharing, and rattles exhibited higher Entropy and Mean Line than the manipulative toys task, where the latter involved exploratory play with toys.

In the models including each temperament variable individually (Models 2, 3, and 4, Table 9), only the fixed effect of the "Manipulative task" (task 2) was a significant predictor of the Mean Line in all models (all $p < .01$). The full model (Model 5, Table 9) demonstrated that the fixed effect of the task was the only significant predictor of Mean Line in infants at 12 months (β = -.56, $p < .01$). This suggests that the task differentiation effect on infants' motor dynamic stability was predominantly relevant at 12 months, in the same way as observed for infants' motor dynamic complexity (Entropy). No significant effects of temperamental variables were observed (H4 was not supported in our sample).

3.5. Longitudinal effects

3.5.1. Predicting motor system complexity (Entropy) at 12 months from temperament at 6 months

Longitudinal models were performed to predict Entropy at 12 months using the temperament variables at 6 months in interaction with task as predictors. Table 10 presents the results of longitudinal mixed-effects models predicting Entropy at 12 months. The models were performed including each temperament variable in a separate model – Negative Affectivity (NEG), Positive Affectivity/Surgency (PAS), and Orienting and Regulatory Capacity (ORC) measured at 6 months, and tasks (task 2, manipulative toys, task 3, rattle-shaking). Also, a full model was performed including all temperament variables (model 4). The intercept of each model represents the baseline of Entropy when engaging in the reference task (task 1, book-sharing). Task 2 (manipulative toys) at 6 months significantly predicted Entropy at 12 months (β = -.59, p < .01 in full model, Table 10). In the short model, Negative Affectivity (NEG) at 6 months had a significant positive effect on Entropy (β = .13, p < .05), indicating that higher levels of Negative Affectivity at 6 months were associated with increased Entropy at 12 months (effect in opposite direction to H1b). Positive Affectivity/Surgency (PAS) and Orienting/Regulatory Capacity (ORC) did not show a significant direct effect on Entropy (H3b and H4b not supported).

3.5.2. Predicting motor system stability (Mean Line) at 12 months from temperament at 6 months

Similarly, longitudinal models were performed to predict, in this case, Mean Line at 12 months using the temperament variables at 6 months in interaction with task as predictors. Table 11 presents the results of longitudinal mixed-effects models examining the predictors of Mean Line, representing infants' motor system stability at 12 months. Again, the models were performed including each temperament variable in a separate model – Negative Affectivity (NEG), Positive Affectivity/Surgency (PAS), and Orienting and Regulatory Capacity (ORC) measured at 6 months, and tasks (task 2, manipulative toys, task 3, rattle-shaking). Next, a full model was tested including all temperament variables. The intercept of each model represents the baseline of Mean Line when engaging in the reference task (task 1, book-sharing). Estimates for task 2 (manipulative toys) and task 3 (rattle-shaking) indicate their effects on Mean Line at 12 months. Task 2 exhibited a significant negative effect on the Mean Line (p < .001) in the individual NEG, ORC, and PAS models, suggesting decreased motor stability (Mean Line) compared to the baseline. Task 3 did not show a significant effect relative to task 1. After correcting for multiple hypothesis testing, there were no significant effects from temperamental variables at 6 months predicting infants' motor system dynamic stability (Mean Line) at 12 months (H2b, H3b, and H4b not supported).

3.6. Maternal Anxiety

As part of an exploratory set of analyses, the effect of maternal trait anxiety (STAI) was included in the prediction of Entropy (complexity) and Mean Line (stability), in addition to temperament and task. Maternal anxiety (STAI) was measured at 4 months of age. We generally expected to find differences in the prediction of Entropy (complexity) and Mean Line (stability) by maternal anxiety.

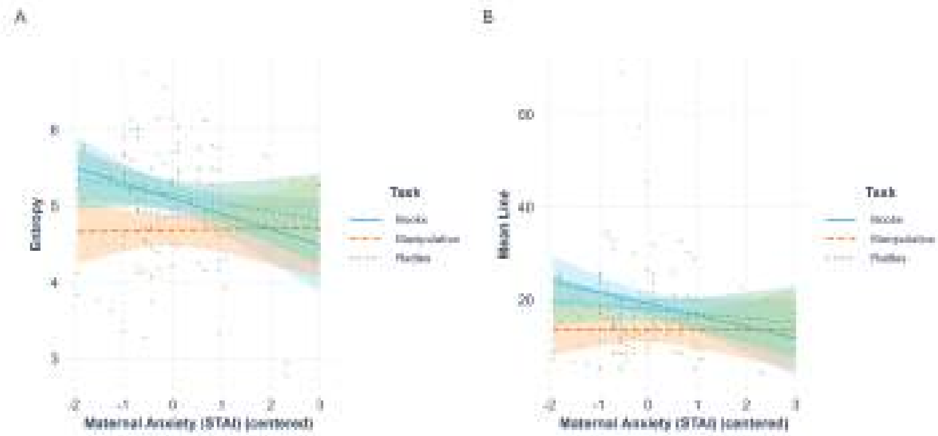
The mixed-effects models for Entropy and Mean Line at 6 months predicted by maternal anxiety (STAI), temperament, and task are presented in Tables 12 and 13. In both cases, there are no specific effects of maternal anxiety on Entropy or Mean Line in any of the models. These results suggest that there are no effects of maternal anxiety on motor system complexity (Entropy) or stability (Mean Line) at 6 months of age in our sample.

Table 14 presents the longitudinal results of mixed-effects models for Entropy at 12 months predicted by maternal anxiety (STAI), temperament, and task. The first model only incorporates maternal anxiety (STAI) and task (task 2: Manipulative toys, task 3: Rattle-shaking with task 1: book-sharing as the baseline). Maternal anxiety exhibited a significant negative effect on Entropy (β = -.33, $p < .05$), suggesting that higher maternal anxiety levels (measured at 4 months) were associated with decreased Entropy (motor system complexity) in infants at 12 months (see Figure 5A). The additive effect of task 2 (Manipulative toys) was significant (β = -.64, $p < .001$) compared to the baseline task 1 (Book-sharing). The influence of maternal anxiety varied depending on the task (manipulative toys) compared to the baseline, emphasizing task-specific associations (STAI*task 2, where task 1 is the baseline, β = .35, $p < .05$). In this case, higher maternal anxiety at 4 months and the manipulative toys task were predictive of decreases in Entropy at 12 months. In this case, H5 was supported but only longitudinally.

Subsequent models incorporate maternal anxiety (STAI, measured at 4 months), temperament variables Negative Affectivity (NEG), Positive Affectivity/Surgency (PAS), and Orienting and Regulatory Capacity (ORC) measured at 6 months, and task on motor Entropy at 12 months of age. Similar effects were observed in the models including NEG, PAS, and ORC, where the negative effects of STAI ($p < .05$ in all models) and task 2 (manipulative toys) ($p < .01$ in all models) were additively significant (see Table 14) (in support of H5).

Finally, the same procedure was conducted to explore the effects of maternal anxiety (STAI, measured at 4 months), task, and temperament on Mean Line (infant's motor system stability) at 12 months. The first model, including maternal anxiety and task, exhibited significant negative effects of maternal anxiety (STAI) in predicting Mean Line (β = -.28, $p < .05$), suggesting that higher maternal anxiety levels at 6 months were associated with decreased motor system stability (Mean Line) at 12 months (see Figure 5B) (in support of H5). This effect was observed in all the models, including temperamental variables. The additive effect of task 2 (manipulative toys) was significant in all models without interacting with STAI ($p < .01$), suggesting that maternal anxiety and the manipulative toys task predicted decreased stability at 12 months. However, these effects seem to separate, not interacting with each other. No further significant effects were observed (see Table 15).

Figure 5. Predicted effects of STAI on Entropy and Mean Line at 12 months



Note: The plots display the longitudinal effects of maternal anxiety (STAI) measured at 4 months on infants' motor system Entropy (Panel A) and Mean Line (Panel B) at 12 months of age across the three different tasks (Books, Manipulative Toys, Rattles). The effect of maternal anxiety (STAI) is statistically significant in predicting Entropy and Mean Line at 12 months (both $p < .05$). The additive effect of the Manipulative Toys task is significant compared to the baseline (Books) ($p < .001$ for Entropy and $p < .01$ for Mean Line). STAI was centered and it represents the standardized scores of the original raw scores. Each unit in the x-axis corresponds to units of standard deviations from the centered mean of '0'. Books = Book-sharing, Manipulative = Manipulative Toys, Rattles = Rattle-shaking.

4. Discussion

Temperament dimensions are thought to reflect stable individual differences in emotional and behavioral reactivity observed during infancy (Tang et al., 2020). Therefore, the differences in temperament should reflect differences in how infants respond to stimulation – which is manifested in changes in the dynamic organization of limb movements. Despite the recognized importance of movement as a key modality through which temperament is expressed in infants (Planalp et al., 2017; Lev-Encab et al., 2022), the understanding of the dynamic organization of limb movements related to temperament dimensions in infancy remains limited. In this study we aimed to address this gap in knowledge by investigating the relationship between temperament dimensions and limb movements in infancy.

We began by examining how temperament dimensions of Negative Affectivity (NEG), Positive Affectivity/Surgency (PAS), and Orienting/Regulatory Capacity (ORC) relate to infant limb movements at 6 and 12 months of age. Infants' spontaneous limb movements were measured with wearable motion trackers during three types of infant-parent interactions: book-sharing, playing with manipulative toys, and rattle-shaking, which differ in task-related demands. We used Multidimensional Recurrence Quantification Analysis (MdRQA) to capture higher-level patterns of infant limb movements, focusing on two MdRQA variables—Entropy, reflecting motor system complexity, and Mean Line, reflecting dynamic stability. Concurrent and longitudinal relationships between temperament dimensions, maternal anxiety, and motor system complexity and stability at both time points were investigated.

Our primary findings regarding the concurrent analyses at 6 and 12 months suggest a relationship between Negative affectivity (NEG) and motor system complexity and stability at an early stage of development (6 months of age). In contrast, at 12 months of age, temperamental variables did not have a significant effect on the motor system, but task-related differences played a major role. Manipulative toys task, which was the least constrained type of play, influenced both Entropy and Mean Line at 12 months. This suggests a robust task-specific effect on infants' motor behavior, showing task-related differences in the limb movement organization at the end of the first year of life (but not at 6 months of age).

Even though in our results we saw associations between body movement and temperament at 6 months of age, the observed effects went in a different direction than anticipated. Contrary to our predictions, Negative Affectivity demonstrated a significant positive association with both Entropy and Mean Line at 6 months, indicating that higher Negative Affectivity was linked to increased complexity (Entropy) and stability (Mean Line). Interestingly, Entropy can be indicative of both complexity or flexibility (e.g., De Jonge-Hoekstra et al., 2020) and irregular or unpredictable dynamics (Shannon, 1948). In this regard, our hypothesis that higher levels of Negative Affectivity would be linked to decreased 'complex' and 'stable' motor behavior, was not supported by our results. Instead, we found the opposite effect – higher Negative Affectivity predicted higher complexity and stability of limb movements. Nevertheless, there are several possibilities to interpret the observed patterns.

Negative Affectivity (NEG) captures individual differences in the tendency to express reactive behavior (Rothbart & Ahadi, 1994; Wittig & Rodriguez, 2019) and reflects infants' distress in response to physical limitations and sudden changes (Gartstein & Rothbart, 2003). Reactive behaviors related to this temperamental dimension are discomfort, fear, anger, sadness, negative facial expressions, and explicit demonstrations of frustration and distress, such as crying (Rothbart & Bates, 2006; Putnam et al., 2008; Olino et al., 2011; Wittig & Rodriguez, 2019). Negative Affectivity can also be interpreted as difficulties in dealing with novelty and high stimulation above the usual threshold.

In early infancy, this is frequently manifested through extensive upper and lower limb movements, with greater speed compared to movements accompanying positive infant affect (Egmose et al., 2019). The association between limb movements and higher Negative Affectivity could indicate actions arising from high levels of stimulation, suggesting a difficulty in processing sensory information (DeSantis et al., 2011; Nakagawa et al., 2016). This interpretation aligns with the observed positive association between Negative Affectivity and Entropy. Coordinated movement is linked to integrated sensory information, or the coupling of perception and action (Gibson, 1979; De Jonge Hoekstra et al., 2016). Thus, more irregular patterns could suggest less developed perception-action integration, which would be in line with a previously reported negative association between Negative Affectivity and behavioral control (Gerardi-Caulton, 2000), as well as a potential difficulty in processing sensory information (Dunn, 2001; Nakagawa et al., 2016). In this sense, critical periods in development would be relevant for understanding the connection between temperament and motor system organization, as we observed the relationship between Negative Affectivity and patterns of movement organization concurrently at 6 months and longitudinally from 6 to 12 months of age, but not concurrently at 12 months. This finding suggests that at 12 months of age there is a likely period of re-organization of motor responses to stimulation, which may conceal an earlier association with Negative Affectivity.

In psychological research, the concept of Entropy is often described as uncertainty or irregularity in the dynamics of complex systems, emerging as a function of competing perceptual and behavioral affordances, and is thought to be experienced as anxiety (Hirsh et al., 2012). In this sense, Entropy, as a continuum, would emerge in "optimal" levels to be a characteristic of adaptive behavior; and in excess can indicate chaotic behavior that is not adaptive anymore. For this reason, it should be interpreted carefully. The positive association between Entropy and Negative Affectivity may reflect increased irregularity in activity of the infant's developing motor system. This is reflected by the motor system's activation and reactivity that characterizes Negative Affectivity, and that has been reliably documented in infants before the age of 9 months of age (Rothbart & Bates, 2006). Moreover, Negative Affectivity is thought to increase during infancy and toddlerhood and to decrease over school years, which can explain why increased Entropy, understood as lower regularity of movement, was observed at 6 months (Sallquist et al., 2009; Cioffi et al., 2021).

The connection between Negative Affectivity and infants' motor system organization may be linked to global changes in the developmental system such as the formation of new large-scale synergies, given the constant exchanges between the developing system and the environment (Adolph & Hoch, 2019). This can occur in the context of developmental cascades, as the dynamics in a specific domain can have wide-ranging effects in other developmental domains over longer time scales (Iverson, 2010; 2021). In this sense, perception and action at early stages of development promote the emergence of more complex forms of behavioral synergies over time, as infants experience a wide range of sensorimotor experiences (Corbetta, 2021). Infants' Negative Affectivity has also been related to maladaptive caregiver-infant relational dynamics, which are linked to maternal negative emotions and intrusiveness, as well as infants' lower socio-emotional skills (An & Kochanska, 2022). These maladaptive caregiver-infant dynamics can interfere with the optimal achievement of developmental milestones by constraining the exploratory behaviors in the environment (Corbetta, 2021; An & Kochanska, 2022). However, it is important to keep in mind the different and sometimes divergent interpretations that the concept of Entropy may have in different contexts and studies, as it has also been linked to children's flexibility and adaptability in previous studies (De Jonge-Hoekstra et al., 2020).

Furthermore, in complex adaptive systems, Entropy is often accompanied by relatively patterned dynamics and stability. This could be one explanation for the higher Mean Line values or stability predicted by Negative Affectivity. However, the link between Negative Affectivity and motor system organization suggests that more research is needed to explore the mechanisms of this association. Temperament is related to an individual's emotional and motor reactivity, it may also affect subsequent social functioning (Calkins, 2012), so it is plausible that higher Entropy might be linked to greater motor activation. In this sense, previous research showed the relationship between Negative Affectivity and maladaptive behavior, internalizing and externalizing problems (e.g., Oldehinkel et al., 2004; Brandes et al., 2018).

Contrary to our expectations, no relationships between Entropy and Mean Line with other temperament dimensions (PAS and ORC) were found. Previous reports suggested that motor coordination may be influenced by effortful control in 3-year-old children (Nakagawa et al., 2016), so the effects of temperament can vary across different developmental periods. The absence of significant effects for Positive Affectivity/ Surgency and Orienting and Regulatory Capacity opens further questions regarding the developmental pathways and specificity of the relation between temperament and early motor development. In this sense, it would be important to explore the effects of different facets of each temperamental dimension, as they can provide more nuanced information about infants' behavior and underlying mechanisms (e.g., Nakagawa et al., 2016). We should also mention that it is important to further explore these relationships with larger samples.

The observed task-specific effects, particularly the influence of playing with manipulative toys on Entropy and Mean Line, indicate task-specificity of movement organization in early motor development. This finding aligns with our expectations of varied motor experiences contributing to motor system outcomes reflecting a task differentiation that emerges with age. We expected higher stability of motor actions during the manipulative toys task compared to other tasks, more rhythmic and stable patterns during rattle-shaking, and less defined motor coordination patterns during book-sharing (i.e., higher Entropy), which involves more vocal than motor actions. In this sense, it is plausible that a less constrained task involves more different possibilities for actions, which results in more variability and lower stability – in contrast to rattle-shaking that promotes highly repetitive, recurrent, and rhythmic movement patterns and book-sharing that elicits more fine-grained manipulation through holding, pointing, and turning pages. The manipulative toys task exhibited the lowest stability and complexity of the three tasks. The observed task effects at 12 months show that the motor system becomes more context-sensitive. More specifically, in complex adaptive systems, system reorganization in response to specific task demands is only possible when the coupling between system components becomes less strict so that the system exhibits flexibility towards those demands (De Jonge-Hoekstra et al., 2020). This seems to be present to a larger degree at 12 months than at 6 months of age. Therefore, our results seem to be aligned with previous findings that showed relations between task-specific effects and the system's specialization in modalities such as speech and gesture (De Jonge-Hoekstra et al., 2016; 2020).

The longitudinal analysis revealed that Negative Affectivity (NEG) at 6 months continued to exert a significant positive effect on Entropy at 12 months, suggesting a persistent effect on the developing motor system. Task demands related to different sets of toys available to infant-parent dyads in different task significantly modified infants' motor system's dynamic complexity and dynamic stability at 12 (but not at 6) months of age. This may reflect a better capacity to flexibly adapt actions to environmental demands and to coordinate body parts onto the appropriate task-specific configurations (functional synergies). This finding emphasizes the importance of considering temperament as a dynamic factor influencing the developmental trajectory of motor skills and studying the mechanisms by which motor system organization is related to temperamental dimensions.

Incorporating maternal trait anxiety provided additional insights. Maternal anxiety (measured when infants were 4 months-old) exhibited a significant negative effect on both Entropy and Mean Line at 12 months (but not at 6 months), indicating a time-dependent association between maternal anxiety and the dynamic organization of infant limb movement across the first year of life. Parenting is acknowledged as a crucial factor influencing children's development, as parents are the primary source of socialization, shaping socio-emotional development (Bornstein, 2002; Wittig & Rodriguez, 2019). In previous studies, high maternal anxiety during pregnancy and early child development have been linked to an increased likelihood of displaying difficulties in achieving developmental milestones assessed by standardized motor and language scales (Kikkert et al., 2010; Irwin et al., 2020; Jeličić et al., 2021). Furthermore, children may express difficulties or adverse trait development when encountering adverse parenting, promoting the development of externalizing and internalizing behaviors (Belsky, 2007; Slagt et al., 2016; Wittig & Rodriguez, 2019). However, it is fundamental to consider that maternal anxiety can be reinforced or a response to the infant's vulnerability and reactivity. This can emerge as a feedback loop between the baseline maternal anxiety and the child's vulnerability that circularly reinforces over time. This needs to be accounted for and explored further.

Overall, our results suggest that temperament, maternal trait anxiety, and task-related demands jointly shape infants' motor system's complexity and dynamic stability. However, each of these factors seems to play a role at different periods of development, with earlier (6 months) and longer-lasting effects of temperamental Negative Affectivity and later (12 months) effects of the task-related context. Finally, the infant's motor system's complexity and dynamic stability at 12 months seem to be further modulated by maternal trait anxiety.

As limitations of our study, we recognize the limited sample size, especially at 12 months of age. On the other hand, given our research questions, we focused on the motor system organization of the infant uniquely, but we understand that the mother (or caregiver) plays a fundamental role in infants' behavior, especially at early developmental stages. Thus, future research should investigate the relationship between dyadic motor synchrony and temperament dimensions. As strengths, we emphasize the longitudinal and experimental design, use of wearable motion trackers to measure spontaneous limb movements, and innovative time series analysis, which open possibilities for future studies. Finally, future research should focus on further understanding the mechanisms by which the dynamic organization of the motor system and temperament dimensions are connected from a developmental perspective on a longer timescale into early childhood.

5. Conclusion

Our findings highlight the interplay between temperament dimensions and motor organization across infancy. Particularly, motor systems' organization – complexity and stability – depend on Negative Affectivity, the type of infant-parent play, and maternal anxiety. Furthermore, our study suggests an effect of temperament on sensorimotor integration and the emergence of motor synergies. Specifically, we observed associations between Negative Affectivity and the complexity and stability of infant limb movements. In this regard, the infant's temperament, maternal anxiety, and situational factors such as different types of play become crucial for understanding how motor coordination patterns develop over sensitive periods for motor development in the first year of life. Further research is needed to understand the underlying mechanisms of these associations and explore their implications for long-term motor, cognitive, and emotional development.

6. Ethics statement and conflict of interest

This study was approved by the Ethics Committee for research with human participants of the Institute of Psychology, Polish Academy of Sciences. The authors declare no conflict of interest related to this research, authorship, or publication.

7. Acknowledgments

We thank all caregivers who participated in the study with their babies. Data collection was funded by the Polish National Science Centre grant no. 2018/30/E/HS6/00214 to Przemysław Tomalski. Zuzanna Laudańska acknowledges further support from the Graduate School for Social Research of the Polish Academy of Sciences and the Polish National Agency for Academic Exchange NAWA STER project (BPI/STE/2021/1/00030/U/00001). Nicol Arellano-Véliz was supported by Agencia Nacional de Investigación y Desarrollo (ANID), Gobierno de Chile (Ph.D. Scholarship 72200122).

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Zuzanna Laudańska: Conceptualization, Methodology, Data Collection, Data Curation, Formal Analysis, Writing-Original Draft. Nicol Arellano-Véliz: Conceptualization, Methodology, Formal Analysis, Visualization, Writing-Original Draft. Joanna Duda-Goławska: Software, Formal Analysis. Ralf Cox: Conceptualization, Writing-Review & Editing, Supervision. Przemysław Tomalski: Conceptualization, Methodology, Funding Acquisition, Writing-Review & Editing, Supervision.

10. Data availability

Further materials such as data and scripts can be accessed at https://osf.io/jbkdw/?view_only=98c437aeb3f9436dbb45ecac0df470ec. Matlab code for movement data preprocessing and MdRQA can be accessed here: https://osf.io/xzt3m/?view_only=5daf73673db7469fb4dac74bc8b931cf

Table 6. Models results for Entropy (infants' motor system complexity) at 6 months predicted by temperament and task

	Model 1: Task (t)		Model 2: NEG		Model 3: PAS		Model 4: ORC		Model 5 Full model	
Fixed effects	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*
Intercept	**5.01(0.06)**	**0.08*****	**5.02(0.06)**	**0.11*****	**5.01(0.06)**	**0.11*****	**5.01(0.06)**	**0.11*****	**5.02(0.06)**	**0.11*****
Task 2: Manipulative	-0.09(0.07)	-0.18	-0.11(0.07)	-0.21	-0.11(0.07)	-0.21	-0.11(0.07)	-0.21	-0.11(0.07)	-0.21
Task 3: Rattle-shaking	-0.02(0.07)	-0.03	-0.05(0.07)	-0.09	-0.04(0.07)	-0.08	-0.04(0.07)	-0.08	-0.04(0.07)	-0.09
NEG			**0.09(0.04)**	**0.17***					0.08(0.04)	0.16.
PAS					0.07(0.04)	0.13			0.03(0.04)	0.07
ORC							0.04(0.04)	0.07	0.04(0.04)	0.07
Random effects	*Var (SD)*		*Var (SD)*		*Var (SD)*		*Var (SD)*		*Var (SD)*	
Level 1, σ^2	0.19(0.43)		0.19(0.43)		0.19(0.43)		0.19(0.43)		0.19(0.43)	
Level 2 Intercept, τ_{00} ID	0.07(0.27)		0.07(0.26)		0.07(0.26)		0.07(0.27)		0.06(0.25)	
ICC	0.28		0.26		0.28		0.28		0.25	
Model fit										
Marginal R^2 / Conditional R^2	0.006/0.282		0.035/0.288		0.013/0.287		0.013/0.287		0.048/0.289	
Observations	251		238		238		238		238	
AIC	369.2		**348.4**		350.1		352.0		350.2	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC) are centered.*

Table 7. Models results for Mean Line (infants' motor dynamic stability) at 6 months predicted by temperament and task

	Model 1: Task (t)		Model 2: NEG		Model 3: PAS		Model 4: ORC		Model 5: Full model	
Fixed effects	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*
Intercept	**15.88(0.64)**	**0.07*****	**16.03(0.64)**	**0.12*****	**15.98(0.65)**	**0.12*****	**15.99(0.66)**	**0.12*****	**16.02(0.64)**	**0.12*****
Task 2: Manipulative	-0.90(0.73)	-0.16	-1.08(0.75)	-0.19	-1.04(0.76)	-0.18	-1.02(0.76)	-0.18	-1.07(0.75)	-0.19
Task 3: Rattle-shaking	-0.41(0.71)	-0.07	-0.73(0.75)	-0.13	-0.71(0.76)	-0.12	-0.71(0.76)	-0.12	-0.73(0.75)	-0.13
NEG			**1.24(0.46)**	**0.21****					**1.24(0.49)**	**0.21***
PAS					0.70(0.46)	0.12			0.24(0.49)	0.04
ORC							0.40(0.47)	0.07	0.49(0.48)	0.09
Random effects	*Var (SD)*		*Var (SD)*		*Var (SD)*		*Var (SD)*		*Var (SD)*	
Level 1, σ^2	21.96(4.69)		21.97		22.13(4.70)		22.05(4.70)		21.96(4.69)	
Level 2 Intercept, τ_{00} ID	10.40(3.23)		9.49		10.19(3.19)		10.68(3.27)		9.14(3.02)	
ICC	0.32		0.30		0.32		0.33		0.29	
Model fit										
Marginal R^2 / Conditional R^2	0.004/0.324		0.050/0.336		0.021/0.329		0.010/0.333		0.061/0.337	
Observations	251		238		238		238		238	
AIC	1572.6		1489.3		1494.0		1495.5		**1488**	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC) are centered.*

Table 8. Models results for Entropy (infants' motor system complexity) at 12 months predicted by temperament and task

	Model 1: task (t)		Model 2: NEG		Model 3: SUR		Model 4: REG		Model 5: Full model	
Fixed effects	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β
Intercept	**5.04(0.09)**	**0.12*** **	**5.06(0.10)**	**0.12*** **	**5.06(0.10)**	**0.11*** **	**5.06(0.10)**	**0.12*** **	**5.05(0.10)**	**0.12*** **
Task 2: Manipulative	**-0.42(0.11)**	**-0.59*** **	**-0.39(0.12)**	**-0.55** **	**-0.39(0.12)**	**-0.55** **	**-0.39(0.12)**	**-0.55** **	**-0.39(0.12)**	**-0.55** **
Task 3: Rattle-shaking	0.11(0.11)	0.16	0.09(0.12)	0.12	0.08(0.12)	0.12	0.08(0.12)	0.12	0.09(0.12)	0.12
NEG			-0.04(0.07)	-0.07					-0.08(0.08)	-0.12
PAS					0.04(0.07)	0.06			0.09(0.09)	0.14
ORC							0.00(0.07)	0.00	-0.04(0.08)	-0.05
Random effects										
Level 1, σ^2	0.34(0.58)		0.33(0.57)		0.32(0.57)		0.33(0.57)		0.32(0.57)	
Level 2 Intercept, τ_{00} ID	0.12(0.35)		0.14(0.37)		0.14(0.38)		0.14(0.38)		0.14(0.37)	
ICC	0.27		0.30		0.31		0.31		0.30	
Model fit										
Marginal R^2 / Conditional R^2	0.102/0.345		0.084/0.361		0.084/0.364		0.080/0.361		0.095/0.367	
Observations	135		135		135		135		135	
AIC	340		**281.8**		281.9		282.2		284.8	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC) are centered.*

Table 9. Models results for Mean Line (infants' motor system dynamic stability) at 12 months predicted by temperament and task

	Model 1: task (t)		Model 2: NEG		Model 3: SUR		Model 4: REG		Model 5: Full model	
Fixed effects	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*
Intercept	**18.48(0.15)**	**0.22*****	**18.73(1.31)**	**0.21*****	**18.74(1.30)**	**0.21*****	**18.70(1.30)**	**0.21*****	**18.65(1.30)**	**0.21*****
Task 2: Manipulative	**-5.41(1.52)**	**-0.61****	**-5.18(1.78)**	**-0.57****	**-5.15(1.77)**	**0.19****	**-5.19**	**-0.57****	**-5.16(1.76)**	**-0.56****
Task 3: Rattle-shaking	-0.59(1.46)	-0.07	-0.89(1.70)	-0.10	-0.90(1.69)	0.18	-0.86	-0.09	-0.85(1.69)	-0.09
NEG			0.05(0.82)	0.01					-0.43(0.92)	-0.05
PAS					0.65(0.84)	0.07			1.39(1.06)	0.16
ORC							-0.53(0.86)	-0.06	-1.17(0.98)	-0.13
Random effects										
Level 1, σ^2	60.44(7.77)		67.32(8.21)		66.79(8.17)		67.24(8.20)		66.13(8.13)	
Level 2 Intercept, τ_{00} ID	12.03(3.47)		11.36(3.37)		11.61(3.41)		11.19(3.35)		11.37(3.37)	
ICC	0.17		0.14		0.15		0.14		0.15	
Model fit										
Marginal R^2 / Conditional R^2	0.073/0.226		0.059/0.195		0.064/0.203		0.062/0.196		0.077/0.212	
Observations	135		135		135		135		135	
AIC	1181.1		982.1		**981.5**		981.7		983.9	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243. **β** = Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC) are centered.*

Table 10. Longitudinal Model results for Entropy (infants' motor system complexity) at 12 months predicted by temperament and task at 6 months

	Model 1: NEG		Model: 2 PAS		Model 3: ORC		Model 4: Full model	
Fixed effects	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*
Intercept	**5.05(0.09)**	**0.13*** **	**5.05(0.09)**	**0.12*** **	**5.05(0.09)**	**0.12*** **	**5.05(0.09)**	**0.12*** **
Task 2: Manipulative	**-0.43(0.11)**	**0.16*** **	**-0.43(0.11)**	**-0.59*** **	**-0.42(0.11)**	**-0.59*** **	**-0.43(0.11)**	**-0.59** **
Task 3: Rattle-shaking	0.11(0.11)	0.15	0.12(0.11)	0.16	0.12(0.11)	0.16	0.12(0.11)	0.17
NEG	**0.19(0.09)**	**0.13* **					0.22(0.10)	0.29
NEG*task 2	-0.12(0.12)	0.16					-0.12(0.12)	-0.16
NEG*task 3	-0.13(0.11)	0.16					-0.20(0.12)	-0.27
PAS			0.03(0.09)	0.04			-0.06(0.10)	-0.08
PAS*task 2			-0.07(0.11)	-0.10			-0.03(0.12)	-0.05
PAS*task 3			0.02(0.11)	0.03			0.15(0.12)	0.22
ORC					0.04(0.08)	0.06	0.09(0.09)	0.13
ORC*task 2					-0.03(0.10)	-0.04	-0.03(0.11)	-0.04
ORC*task 3					-0.13(0.10)	-0.20	-0.21(0.11)	-0.32
Random effects								
Level 1, σ^2	0.33(0.58)		0.33(0.58)		0.33(0.57)		0.31(0.56)	
Level 2 Intercept, τ_{00} ID	0.12(0.34)		0.13(0.36)		0.13(0.36)		0.13(0.36)	
ICC	0.26		0.28		0.28		0.29	
Marginal R^2/Conditional R^2	0.128/0.355		0.106/0.354		0.110/0.360		0.148/0.393	
Observations	164		164		164		164	
AIC	**340.8**		344		342.9		347.8	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC) are centered.*

Table 11. Longitudinal Model results for Mean Line (infants' motor system stability) at 12 months predicted by temperament and task at 6 months

	Model 1: NEG		Model 2: PAS		Model 3: ORC		Model 4: Full model	
Fixed effects	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β
Intercept	**18.56(1.14)**	**0.22*** **	**18.50(1.15)**	**0.13*** **	**18.49(1.15)**	**0.22*** **	**16.04(0.64)**	**0.12*** **
Task 2: Manipulative	**-5.47(1.52)**	**-0.61*** **	**-5.45(1.53)**	**-0.61*** **	**-5.40(1.52)**	**-0.61*** **	-1.12(0.74)	-0.19
Task 3: Rattle-shaking	-0.58(1.46)	-0.06	-0.50(1.47)	-0.06	-0.52(1.46)	-0.06	-0.76(0.74)	-0.13
NEG	1.92(1.19)	0.21					1.45(0.70)	0.25
NEG*task 2	-1.59(1.55)	-0.17					0.13(0.81)	0.02
NEG*task 3	-1.66(1.53)	-0.18					-0.76(0.82)	–0.13
PAS			0.20(1.13)	0.02			-0.26(0.69)	-0.05
PAS*task 2			-0.43(1.46)	-0.05			1.18(0.81)	0.21
PAS*task 3			0.17(1.45)	0.02			0.34(0.80)	0.06
ORC					0.45(1.05)	0.06	0.74(0.68)	0.12
ORC*task 2					-0.28(1.38)	-0.03	-0.05(0.79)	-0.01
ORC*task 3					-1.07(1.34)	-0.13	-0.69(0.80)	-0.12
Random effects								
Level 1, σ^2	59.91(7.74)		60.38(7.77)		59.96(7.74)		21.21(4.61)	
Level 2 Intercept, τ_{00} ID	11.68(3.42)		12.40(3.52)		12.70(3.56)		9.34(3.06)	
ICC	0.16		0.17		0.17		0.31	
Marginal R^2 /Conditional R^2	0.089/0.237		0.074/0.232		0.076/0.238		0.077/0.359	
Observations	164		164		164		164	
AIC	**1178.1**		1180.5		1180.0		1497.9	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC) are centered.*

Table 12. Models results for Entropy (infants' motor system complexity) at 6 months predicted by maternal anxiety (STAI), temperament and task

	Model 1: STAI		Model 2: NEG		Model 3: PAS		Model 4: ORC		Model 5: Full model	
Fixed effects	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*
Intercept	5.01(0.06)	**0.08*** **	**5.03(0.06)**	**0.11*** **	**5.02(0.06)**	**0.11*** **	**5.02(0.06)**	**0.11*** **	**5.03(0.06)**	**0.11*** **
STAI	-0.01(0.06)	-0.01	-0.04(0.06)	-0.08	-0.03(0.06)	-0.07	-0.03(0.06)	-0.05	-0.04(0.06)	-0.09
Task 2: Manipulative	-0.10(0.07)	-0.20	-0.12(0.07)	-0.23	-0.12(0.07)	-0.23	-0.12(0.07)	-0.22	-0.12(0.07)	-0.23
Task 3: Rattle-shaking	-0.00(0.07)	-0.00	-0.04(0.07)	-0.06	-0.03(0.07)	-0.06	-0.03(0.07)	-0.06	-0.04(0.07)	-0.06
STAI*task 2	-0.01(0.07)	-0.01	0.02(0.07)	0.03	0.02(0.07)	0.03	0.01(0.07)	0.03	0.01(0.07)	0.03
STAI*task 3	0.04(0.07)	0.08	0.07(0.07)	0.14	0.07(0.07)	0.13	0.06(0.07)	0.13	0.07(0.07)	0.14
NEG			**0.10(0.04)**	**0.19***					**0.11(0.04)**	**0.20***
PAS					0.07(0.04)	0.15			0.03(0.04)	0.06
ORC							0.05(0.04)	0.10	0.06(0.04)	0.12
Random effects										
Level 1, σ^2	0.19(0.44)		0.19(0.43)		0.19(0.44)		0.19(0.43)		0.19(0.43)	
Level 2 Intercept, τ_{00} ID	0.07(0.26)		0.06(0.25)		0.06(0.25)		0.07(0.26)		0.06(0.24)	
ICC	0.27		0.25		0.25		0.27		0.23	
Marginal R^2/Conditional R^2	0.011/0.276		0.048/0.283		0.033/0.279		0.022/0.283		0.072/0.285	
Observations	242		229		229		229		229	
AIC	361.2		**338.8**		341.4		343.1		338.9	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC, STAI) are centered.*

Table 13. Models results for Mean Line (infants' motor system stability) at 6 months predicted by maternal anxiety (STAI), temperament and task

	Model 1: STAI		**Model 2: NEG**		**Model 3: PAS**		**Model 4: ORC**		**Model 5: Full model**	
Fixed effects	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β
Intercept	**15.92(0.65)**	**0.09*** **	**10.57(1.95)**	**0.12*** **	**16.06(0.67)**	**0.12*** **	**16.04(0.67)**	**0.12*** **	**16.10(0.65)**	**0.12*** **
STAI	-0.06(0.62)	-0.01	-0.43(0.63)	-0.08	-0.31(0.64)	-0.06	-0.24(0.64)	-0.04	-0.44(0.62)	-0.08
Task 2: Manipulative	-0.94(0.75)	-0.17	-1.15(0.77)	-0.20	-1.10(0.78)	-0.19	-1.08(0.78)	-0.19	-1.14(0.77)	-0.20
Task 3: Rattle-shaking	-0.34(0.75)	-0.06	-0.70(0.77)	-0.11	-0.67(0.78)	-0.11	-0.67(0.78)	-0.11	-0.69(0.77)	-0.11
STAI*task 2	-0.18(0.73)	-0.03	0.04(0.74)	0.01	0.02(0.75)	0.00	-0.00(0.75)	-0.00	0.02(0.74)	0.00
STAI*task 3	0.57(0.72)	0.10	0.80(0.74)	0.14	0.78(0.74)	0.14	0.74(0.74)	0.13	0.79(0.74)	0.14
NEG			**1.52(0.51)**	**0.24** **					**1.51(0.50)**	**0.26** **
PAS					0.79(0.47)	0.14			0.23(0.49)	0.04
ORC							0.55(0.48)	0.10	0.77(0.49)	0.13
Random effects										
Level 1, σ^2	22.17(4.71)		22.21(4.74)		22.37(4.73)		22.26(4.72)		22.17(4.71)	
Level 2 Intercept, τ_{00} ID	10.39(3.22)		9.05(3.01)		10.03(3.17)		10.55(3.25)		8.37(2.89)	
ICC	0.32		0.29		0.31		0.32		0.27	
Marginal R^2/Conditional R^2	0.008/0.325		0.065/0.336		0.028/0.239		0.019/0.335		0.087/0.337	
Observations	242		229		229		229		229	
AIC	1524.3		**1439.4**		1445.2		1446.7		1439.9	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC, STAI) are centered.*

Table 14. Models results for Entropy (infants' motor system complexity) at 12 months predicted by maternal anxiety (STAI), temperament and task

	Model 1: STAI		Model 2: NEG		Model 3: PAS		Model 4: ORC		Model 5: Full model	
Fixed effects	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β	Estimate(SE)	β
Intercept	**5.08(0.09)**	**0.16*** **	**5.10(0.10)**	**0.16*** **	**5.10(0.10)**	**0.16*** **	**5.10(0.10)**	**0.16*** **	**5.09(0.10)**	**0.16*** **
STAI	**-0.22(0.09)**	**-0.33***	**-0.20(0.10)**	**-0.30***	**-0.22(0.10)**	**-0.33***	**-0.22(0.09)**	**-0.32***	**-0.20(0.10)**	**-0.30***
Task 2: Manipulative	**-0.45(0.12)**	**-0.64*** **	**-0.41(0.13)**	**-0.60** **	**-0.41(0.13)**	**-0.60** **	**-0.41(0.13)**	**-0.60** **	**-0.41(0.13)**	**-0.60** **
Task 3: Rattle-shaking	0.08(0.11)	0.11	0.05(0.12)	0.32	0.05(0.12)	0.32	0.05(0.12)	0.06	0.05(0.12)	0.06
STAI*task 2	0.23(0.11)	0.35*	0.21(0.12)	0.32	0.21(0.12)	0.32	0.21(0.12)	0.32	0.21(0.12)	0.32
STAI*task 3	0.11(0.10)	0.17	0.09(0.11)	0.14	0.09(0.11)	0.14	0.09(0.11)	0.14	0.09(0.11)	0.14
NEG			-0.04(0.08)	-0.06					-0.07(0.08)	-0.10
PAS					0.03(0.07)	0.05			0.08(0.09)	0.11
ORC							-0.01(0.07)	-0.01	-0.04(0.08)	-0.05
Random effects										
Level 1, σ^2	0.33(0.57)		0.31(0.56)		0.31(0.56)		0.31(0.56)		0.31(0.56)	
Level 2 Intercept, τ_{00} ID	0.12(0.34)		0.12(0.35)		0.13(0.36)		0.13(0.36)		0.12(0.35)	
ICC	0.26		0.28		0.29		0.29		0.28	
Marginal R^2/Conditional R^2	0.150/0.373		0.132/0.378		0.132/0.382		0.130/0.380		0.140/0.384	
Observations	156		129		129		129		129	
AIC	322.3		**268.9**		**268.9**		269.1		272.1	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* $\boldsymbol{\beta}$ *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC, STAI) are centered.*

Table 15. Models results for Mean Line (infants' motor system stability) at 12 months predicted by maternal anxiety (STAI), temperament and task

	Model 1: STAI		Model 2: NEG		Model 3: PAS		Model 4: ORC		Model 5: Full model	
Fixed effects	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*	Estimate(SE)	*β*
Intercept	**18.96(1.17)**	**0.25*** **	**19.14(1.32)**	**0.25*** **	**19.13(1.32)**	**0.24*** **	**19.12(1.32)**	**0.24*** **	**19.07(1.32)**	**0.24*** **
STAI	**-2.39(1.10)**	**-0.28***	-2.47(1.30)	-0.28.	**-2.51(1.26)**	**-0.29***	-2.42(1.26)	-0.28	-2.47(1.29)	-0.28.
Task 2: Manipulative	**-5.82(1.58)**	**-0.66****	**-5.51(1.84)**	**-0.61****	**-5.48(1.83)**	**-0.61****	**-5.53(1.83)**	**-0.61****	**-5.50(1.82)**	**-0.61****
Task 3: Rattle-shaking	-0.95(1.52)	-0.11	-1.24(1.75)	-0.14	-1.25(1.74)	-0.14	-1.22(1.75)	-0.14	-1.20(1.73)	-0.14
STAI*task 2	2.38(1.48)	0.28	2.53(1.75)	0.29	2.53(1.74)	0.29	2.49(1.75)	0.28	2.47(1.73)	0.28
STAI*task 3	1.42(1.42)	0.17	1.51(1.65)	0.17	1.53(1.65)	0.17	1.48(1.65)	0.17	1.51(1.64)	0.17
NEG			0.11(0.91)	0.01					-0.33(1.00)	-0.04
PAS					0.59(0.84)	0.06			1.28(1.04)	0.14
ORC							-0.61(0.84)	-0.07	-1.19(0.96)	-0.13
Random effects										
Level 1, σ^2	61.38(7.84)		68.07(8.25)		67.55(8.22)		68.04(8.25)		66.86(8.18)	
Level 2 Intercept, τ_{00} ID	10.46(3.23)		9.14(3.02)		9.44(3.07)		8.80(2.97)		9.16(3.03)	
ICC	0.15		0.12		0.12		0.11		0.12	
Marginal R^2/Conditional R^2	0.109/0.239		0.095/0.202		0.098/0.209		0.099/0.202		0.111/0.219	
Observations	156		129		129		129		129	
AIC	1122.7		943.2		942.8		**942.7**		945.2	

*Note: task 1 (book-sharing) was considered the baseline; task 2 (Manipulative toys); task 3 (Rattle-shaking). AIC = Akaike's Information Criterion (lower values indicate better fit, best fit in boldface). Bold text indicates statistically significant effects; 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Ni = 83. Number of observations: 243.* ***β*** *= Standardized beta. NEG= Negative Affectivity, PAS= Positive Affectivity/Surgency, ORC= Orienting/Regulatory Capacity. Predictors (NEG, PAS, ORC) are centered.*

Chapter 7

General Discussion

The main aim of this thesis was to explore the fluid and adaptive qualities of personality, particularly by its manifestation through embodied dynamics at intra-individual and interpersonal levels, the engagements with the world, and the synchronizing mechanisms underpinning these processes. This aim was extended to temperament in infancy. The key questions guiding this dissertation were presented as follows: How do dynamic bodily and speech patterns reflect the interplay between personality traits, temperament, interpersonal synchronization, and environmental interactions?

The thesis started by outlining an integrative approach of enactive, embodied, and complex dynamical systems perspectives to understanding personality traits (Chapter 2) which provided a theoretical landscape that was at the base of the thesis but also extended beyond the scope of the experimental studies conducted and proposes some future lines of research. Then, the role of embodied dynamics both at interpersonal and individual levels in young adults was studied in Chapters 3, 4, and 5. This approach was then expanded to the study of temperament and motor system organization in Chapter 6. The findings across these chapters provide robust evidence for the connection between personality traits and dynamic behavioral patterns, showing that embodied dynamics in behavioral patterns are fundamentally connected to the expression and development of psychological traits. This chapter will synthesize these findings, and techniques employed, discuss their theoretical implications, and suggest directions for future research.

Summary of chapters

Integrative Perspectives on Enactive, Embodied, and Complex Systems Applied to Personality Science (Chapter 2)

Chapter 2 of this dissertation proposed an integrative enactive, embodied, and complex dynamical systems approach as a fundamental framework for understanding personality traits. It suggests that regularities, dynamics, and stylistic differences characterize personality traits, and explores how these perspectives can capture personality traits by examining the patterns and interactions between embodied individuals and their environments. The enactive approach emphasizes the connection between life and the human mind, while embodiment emphasizes the link between an individual's physical constitution and their interaction with the environment. The complex dynamical system theory provides a methodological toolbox for studying behavior patterns over time and situations, as well as the concept of synchronization. The chapter introduces the Skilled Intentionality Framework (SIF, Rietveld et al., 2018), which explains how individuals perceive and act upon (enact) relevant affordances, and proposes that personality traits influence an individual's embodied readiness to engage (synchronize) with different affordances. The concepts of multistability and metastability within complex dynamical systems are discussed as potential mechanisms for the engagement with multiple affordances and the adaptability and coherence of personality traits over different time scales. The chapter concludes by emphasizing the importance of exploring how different aspects of embodiment contribute to the development and expression of personality traits and other psychological traits.

The interacting partner as the immediate environment: Personality and interpersonal dynamics (Chapter 3)

In Chapter 3 we explored the dynamics of interpersonal synchronization of body motion during conversations. We examined how the social personality traits Extraversion and Agreeableness, influence synchronization. We analyzed the impact of different conversation topics on synchronization patterns, as reported in the literature (e.g., Paxton & Dale, 2013), and investigated how synchronization predicted outcomes like interpersonal closeness, affect, and enjoyment. For this, 112 undergraduate students (56 same-sex dyads) participated in 15-minute conversations divided into three parts: introductions, self-disclosure, and argumentative. Conversations were video recorded, and Motion Energy Analysis (MEA, Ramseyer, 2020) was used to extract the time series. Synchronization strength was measured using Windowed Lagged Cross-Correlations (WLCC), and dynamic organization was analyzed using Cross-Recurrence Quantification Analysis (CRQA) through the variables of Determinism (deterministic patterns), Entropy (complexity), Laminarity (laminar states) and Mean Line (stability).

The results showed that Extraversion and Agreeableness significantly were connected to interpersonal synchronization. In the models performed, high Extraversion predicted stronger synchronization and positive interaction appraisals. Dyads with similar Extraversion scores exhibited stronger synchronization, especially during self-disclosure, while introverts showed weaker synchronization. Mixed dyads (low/high Extraversion) exhibited stable dyadic coupling during argumentative conversations. Stronger, more stable dyadic coupling was observed in extroverts, particularly when interacting with introverts. Moments of shared and fixated interpersonal states (laminar states) led to more enjoyable conversations in dissimilar dyads. Agreeableness predicted higher Entropy in dynamic coupling and lower negative affect post-interaction. Higher Entropy indicated greater interaction complexity and variety in coupling patterns, which can reflect the flexibility and spontaneity of agreeable individuals. Agreeable individuals seemed to have displayed more adaptive and responsive behaviors, creating engaging and flexible interaction environments, while less agreeable individuals exhibited more rigid and more deterministic behaviors.

Personality expression in body motion dynamics: An enactive, embodied, and complex systems perspective (Chapter 4)

In Chapter 4 the relationship between personality traits and body motion dynamics was explored during an individual self-referencing task. 105 participants spoke about themselves for 15 minutes on three topics: introducing themselves, bodily perception and sensory life, and socio-emotional life. Body motion dynamics were measured using Recurrence Quantification Analysis (RQA), which extracted variables such as Determinism, Entropy, Laminarity, and Mean Line. Body motion dynamics were viewed as indicators of self-organizing dynamics (Kelso, 2001). It was expected that individual differences in personality traits would explain variations in these dynamics. For instance, Neuroticism was anticipated to predict more disorganized dynamics due to its association with low emotional stability, defensive responses, and anxious feelings (DeYoung, 2015). In contrast, traits like Extraversion, Agreeableness, Conscientiousness, and Openness were expected to predict more organized dynamics.

The results showed that Neuroticism predicted lower Determinism and more fluctuating dynamics, indicating less stable and more variable body motion, particularly when talking about their bodily perception and socio-emotional life. High Neuroticism also correlated with higher negative affect after the task. Extraversion was associated with more regular and deterministic motion patterns during the bodily perception and sensory life topic. Conscientiousness was linked to lower Determinism regardless of the topic. These findings support the idea that personality traits influence physical self-expression and environmental interaction and that different personality traits interact differentially with environmental constraints. This study also evidenced the impact of high-level constraints (the self-referencing topics) on body motion dynamics. Participants reported less negative affect after the task, suggesting that self-disclosure generally improves affect state, except for those with high Neuroticism. Body motion dynamics reflect self-organizing processes indicative of underlying sensations, feelings, thoughts, memories, emotions, and meaning (Gallagher & Daly, 2018; Di Paolo, 2021).

Beyond Words: Speech Synchronization and Conversation Dynamics Linked to Personality and Appraisals (Chapter 5)

Chapter 5 extends the study from Chapter 3, focusing on the nonverbal dimension of speech synchronization, leading-following dynamics, and nonverbal dominance. The social personality traits of Extraversion and Agreeableness, as well as interaction appraisals, were also studied. A subsample of 100 participants (50 same-gender dyads) engaged in the conversation described in Chapter 3. Functional synchronization focused on turn-taking dynamics and conversational rhythm, emphasizing reciprocity (Reuzel et al., 2013). The analyses employed included Categorical Cross-Recurrence Quantification Analysis (CRQA), Diagonal Cross-Recurrence Profiles (DCRP), and Anisotropic-CRQA. Five variables were measured: global speech synchronization (RR_{global}), speech synchronization at lag-zero (RR_{LOS}), leading-following dynamics (Q_{DCRP}), and asymmetries in nonverbal interactional dominance by extent (LAM_{ARD}) and duration (TT_{ARD}). Interaction appraisals were assessed with a questionnaire.

Key findings indicated that speech synchronization and nonverbal dominance varied across topics, with higher global speech synchronization during argumentative conversations. This supports the role of conversational topics in influencing speech synchronization, in line with previous research (Fusaroli et al., 2014). High Extraversion was linked to increased speech synchronization across topics (Costa & McCrae, 1995; Lucas & Diener, 2001). Dyads with similar Extraversion levels exhibited more symmetrical turn-taking during self-disclosure, and the presence of at least one extravert led to increased synchronization. Extraverts valued swift conversations, while introverts appreciated silences and pauses. Introverts predicted nonverbal interactional dominance by using their partner's behavior as a guide. High Agreeableness was associated with reduced speech synchronization in argumentative conversations, while low Agreeableness showed higher synchronization in these contexts, similar to Chapter 3. Increased lag-zero synchronization was linked to a lower perception of naturalness among agreeable individuals, suggesting a trade-off between rapid speech dynamics and conversational flow. Agreeable individuals demonstrated sustained nonverbal dominance during self-disclosure and argumentation, facilitating prosocial and reciprocal interactions (Worgan & Moore, 2011).

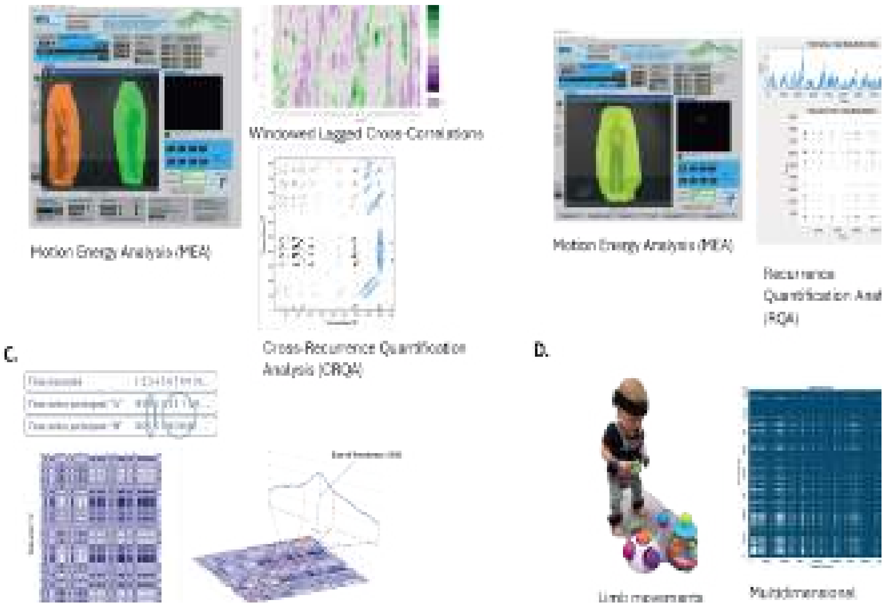
Relationship between temperamental dimensions and infant limb movement complexity and dynamic stability (Chapter 6)

Chapter 6 investigated temperamental associations with high-level measures of motor system organization at 6 and 12 months of age. The study included maternal trait anxiety to examine the effects of caregiver mental well-being. In a longitudinally studied sample of 83 (at 6 months) and 59 (at 12 months) infants, their limb movements were measured with wearable accelerometers during three types of play with their caregiver (book sharing, manipulative toys, and rattle-shaking). Multidimensional Recurrence Quantification Analysis (MdRQA) was conducted to extract the variables of Entropy and Mean Line, providing information about motor systems' complexity and stability, respectively. Using mixed-effects models, we evaluated the predictive effect of task and temperamental variables: Negative Affectivity (NEG), Positive Affectivity or Surgency (PAS), and Orienting and Regulatory Capacity (ORC).

Our results indicated that Negative Affectivity predicted increased motor system Entropy and Mean Line at 6 months and longitudinally at 12 months. Temperament variables measured at 12 months did not predict motor system complexity and stability at the same age. However, at 12 months, Entropy and Mean Line were modulated by task. Additionally, higher maternal anxiety (measured when the infants were 4 months old) predicted decreased motor system Entropy and Mean Line at 12 months. These findings have implications for understanding the early developmental pathways of motor system organization, its relationship with temperament, and the influence of caregiver mental health on infant motor development.

In the following sections, I will provide an integration of the results of the previous chapters, their convergencies, and implications. Furthermore, I will cover the methods employed in this thesis, how they contributed to meaningful findings, and also the improvements that can be made in the future.

Figure 1. Representation of the empirical studies of this dissertation



Note: The image represents the four experimental studies included in this dissertation. Panel A visually represents Chapter 3, where interpersonal synchronization of body motion was explored using Motion Energy Analysis (MEA), Windowed Lagged Cross-Correlations, and Cross-Recurrence Quantification Analysis (CRQA) linked to the personality traits of Extraversion and Agreeableness. Panel B represents Chapter 4, where body motion dynamics (MEA) at the individual level were explored using Recurrence Quantification Analysis (RQA) linked to the Big Five personality traits. Panel C represents Chapter 5, where speech synchronization was explored using Categorical CRQA, Anisotropic CRQA, and Diagonal Cross-Recurrence Profiles, linked to Extraversion and Agreeableness. Panel D represents Chapter 6, where limb movement organization was studied in infants through Multidimensional RQA (MdRQA) and connected to temperament dimensions (figures in Panel D were adapted from Laudańska, 2024).

Synchronization at different levels of analysis and environmental constraints

One of the fundamental assumptions/starting points throughout this thesis is that the human body continuously enacts its physical surroundings, creating a network of feedback loops and sensorimotor couplings that embed sensorimotor life within its immediate environment (e.g., Maturana & Varela, 1991; Pfeifer & Bongard, 2006; Da Rold, 2018). The individual is coupled with the environment, and in synergy, the individual-environment system emerges as an integrated whole by means through the mechanism of synchronization (e.g., Nowak et al., 2020).

Synchronization, the coordination of elements in humans and other living systems (Nowak et al., 2017; Thelen & Smith, 1994), was presented as a fundamental and functional mechanism at different levels and time scales to understand how the coupling between individual and environment occurs. Importantly, synchronization was not merely described as a type of coordination, but as a fundamental self-organizing mechanism at the base of different levels of physiological, cognitive, affective, behavioral, and social functioning (see Nowak et al., 2017; 2020). According to the literature, synchronization is a fundamental aspect of social interactions (e.g., Richardson & Dale, 2005; Tschacher et al., 2018; Galbusera et al., 2019) and individual functioning (Nowak et al., 2017; 2020). In this thesis, the emergence of interpersonal synchronization in dyadic interactions varied depending on both the interacting partner's personality traits and conversational topics or high-level constraints (Chapters 3 and 5). In this sense, previous studies explored the predictive effects of personality on nonverbal interpersonal synchronization (Tschacher et al., 2018) and high-level constraints (Paxton & Dale, 2013). However, the interactive effects of personality traits of each interacting partner on interpersonal synchronization of body motion and speech is a novel approach. This is fundamental to explore how different dyadic compositions lead to different outcomes not only in how the dyad behaves as a whole (synchronized); but also how such dyadic compositions in combination with the emergent dynamics of the interaction promote different subjective experiences for each interacting partner.

It is relevant to mention that previous studies have shown that personality traits in dyadic interactions are relevant to the appraisals of both interacting partners (e.g., Cuperman & Ickes, 2009). However interpersonal dynamics in connection to personality traits at the embodied level and employing dynamic measures, as presented in this thesis, is a novel approach.

Interpersonal synchronization of body motion and speech: Personality and dyadic interactions

The approach of Chapters 3 and 5 was that each interacting partner was conceptually understood as the immediate environment of the other (e.g., Asendorpf, 2017; Vallacher et al., 2002; Nowak et al., 2020). Particularly these studies examined how the composition of the dyads in terms of similarity and dissimilarity in personality scores (of the socially relevant traits, Extraversion, and Agreeableness) impacted interpersonal synchronization and the appraisals of the interaction. The rationale was that the personality traits of each member of the dyad (elements of each system) would contribute to the interaction, promoting the emergence of novel properties. These novel properties were expressed through the interpersonal synchronization of body motion and speech dynamics, and in post-interaction appraisals. This emergence may occur because the coupling of these individual systems formed a more complex dyadic system with fewer degrees of freedom than the sum of those of the individual ones (Dale et al., 2011; Ramenzoni et al., 2012; Tschacher et al., 2018).

Overall, Extraversion seemed to reflect behavioral patterns associated with greater synchronization. Extraverts seemed to engage in synchronous interactions naturally and experience such encounters positively, whereas introverts exhibited weaker synchronization overall. In Chapter 3, dyads with similar Extraversion scores in both interacting partners exhibited stronger synchronization (turn-taking), especially when self-disclosing, while introverts generally exhibited weaker synchronization. Mixed dyads (low and high Extraversion) exhibited stable dyadic coupling during the argumentative conversation, expressed by Mean Line (average duration of episodes of dyadic attunement in bodily movements, McCamley, 2017). Stronger and more stable dyadic coupling was observed in extroverted individuals, especially when interacting with introverts. Furthermore, the presence of laminar states (fixated states) in dissimilar dyads resulted in more enjoyable conversations, suggesting that such moments of shared interpersonal states are relevant, especially in dissimilar dyads. Whereas extroverted dyads appraised flexible and swift dynamics (less laminar states) as enjoyable.

In Chapter 5, Extraversion was associated with increased speech synchronization, with extraverts showing more context-independent interpersonal speech dynamics (Costa & McCrae, 1995; Lucas & Diener, 2001). Dyads with similar levels of Extraversion exhibited more symmetrical turn-taking dynamics during self-disclosure, and the presence of at least one extravert in the dyad led to increased synchronization, in alignment with the results of Chapter 3. Highly extroverted individuals valued positive speech synchronization and swift conversations, while introverts value the presence of silences and pauses more. This adds to the results found in Chapter 3, where more laminar (fixated) states only were enjoyed in mixed dyads, but not in those composed of extroverts. Nonverbal interactional dominance, particularly in introverts, is predicted using the partner's behavior as a guide and aligning with their cues, which can be positive for introverts in the interaction, as they might have used the opportunities created by extroverts.

Agreeableness predicted higher Entropy in the dynamic organization between interacting partners, and lower negative affect after the interaction. Higher Entropy was thought to reflect the dynamic complexity of interactions, capturing the variety of coupling patterns between participants (Marwan et al., 2007). Agreeable individuals exhibited more complex and less deterministic movement patterns, suggesting greater flexibility and spontaneity in their interactions, which can be understood in the light of the tendency of agreeable individuals to cooperate with others and adapt their behavior (Ashton & Lee, 2007; Cuperman & Ickes, 2009). This aligns with prior research linking Agreeableness to dynamic movement patterns (Koppensteiner, 2013), and can reflect adaptive and responsive interactional patterns. In Chapter 5, high Agreeableness was associated with reduced speech synchronization in argumentative conversations, and low Agreeableness exhibited higher speech synchronization during argumentative conversations, similar to what was observed in Chapter 3. Increased speech synchronization (at lag-zero) was connected to a lower perception of naturalness among agreeable individuals. This finding suggests a possible trade-off between maintaining rapid speech dynamics and the natural flow of conversation for highly agreeable individuals. Interestingly, larger duration in episodes of nonverbal interactional dominance and greater leading behavior was observed in agreeable individuals during self-disclosing and argumentative conversations suggesting sustained influence and nonverbal interactional dominance, which in the case of agreeable individuals can facilitate prosocial and reciprocal interactions (Worgan & Moore, 2010).

In terms of the functionality of interpersonal synchronization, it is likely that extraverts not only perceive and use social opportunities for action (i.e. social affordances) for themselves, but at the same time intentionally and unintentionally (or reflective and pre-reflective) create them for people around them (e.g., Augustine & Hemenover, 2008; 2012; de Vries et al., 2016; Back et al., 2023). This effect was evident not only in dyads composed of extroverts but also in mixed dyads of introverted and extroverted individuals, which exhibited higher synchronization and more positive outcomes than dyads of introverted individuals. Agreeable individuals appear to engage in more active perception-action cycles during synchronization episodes, demonstrating greater adaptability and exploration. In contrast, less agreeable individuals showed more rigid and predictable behaviors, as well as higher negative affect after the interaction. The observed link between Agreeableness and interaction complexity suggests that agreeable individuals can foster more engaging and flexible interaction environments.

In the case of extroverted individuals, this effect aligns with the dopaminergic mechanism reported in the literature, by which extroverts tend to engage in external social stimulation, linked to a higher threshold for social stimulation (DeYoung, 2013).

However, it is crucial to be cautious about the causality of behavioral, affective, and cognitive patterns of personality. Rather than suggesting direct causation by personality traits such as Extraversion and Agreeableness, it is plausible that individuals develop synchronization-related skills and habits that are socially rewarding and stimulating, which are reinforced over time (e.g., Nowak et al., 2020; Satchell et al., 2021). These behaviors become strong attractors within the individual's behavioral system, reinforcing and further developing these tendencies over time. This dynamic process contributes to the formation of traits that we recognize as the Big Five personality traits (or other classifications). These traits are subsequently identified through personality assessments designed to capture self-reported and self-observed behavioral patterns. Furthermore, our conceptualization and recognition of these traits are influenced by the labels present in the literature we use to describe the regularities observed in social interactions.

Intra-individual (functional) synchronization

At the individual level, synchronization was explored mainly in Chapter 4 and partially in Chapter 6. In Chapter 4, body motion dynamics were understood as an element that provided information about the self-organizing dynamics of the participants during an individual self-referencing task. Self-organization refers to the process by which system components spontaneously form ordered patterns and structures without internal or external direction (Kelso, 2001). This concept provides a framework to connect the brain, mind, and environment, suggesting that the creation and evolution of patterned behavior—from neural activity to cognitive processes and behavior—are governed by these self-organizing principles (Kelso, 1995).

Personality and self-organizing dynamics in adults

Self-organizing dynamics were operationalized in Chapter 4 through the variables of Determinism (deterministic patterns), Entropy (complexity), Laminarity (laminar states/ phases), and Mean Line (stability) were thought to inform about the coordination of elements at the individual level (intra-personal synchronization). It was expected to find differences in such dynamics explained by individual differences in personality traits and self-referencing topics. A remarkable aspect of this study was that Neuroticism (emotional stability), was anticipated to predict disorganized dynamics. The reason for this anticipation was that low emotional stability, defensive responses, and anxious feelings that characterize Neuroticism (e.g., DeYoung, 2015), can be expressed and captured in the emergent body motion patterns. Whereas for traits such as Extraversion, Agreeableness, Conscientiousness, and Openness, the opposite was expected.

Interestingly, Neuroticism was the dimension that exhibited the most pronounced effects in the models performed in this study, being linked to both low complexity and stability of body motion when talking about themselves, especially about their socio-emotional life. Extraversion and the self-referencing tasks also led to changes in the bodily dynamics, whereas the effects found for Conscientiousness were unrelated to the topics. The expression of Neuroticism in body motion self-organization is a relevant finding since this dimension has been mainly described in the literature in terms of "intrinsic" dynamics, where individuals are more likely to experience feelings of anxiety, depression, irritability, and emotional instability (Watson, 2001). People high in Neuroticism are also described in the literature as more prone to experience stress and have difficulty coping with life's challenges (Ng, 2015). In this sense, we succeeded in capturing these characteristics in dynamic body motion patterns together with negative affect after the task, which sets an optimistic precedent for future studies focusing on embodied dynamics. This is relevant considering that Neuroticism is consistently reported as a predictor of a variety of life outcomes, such as well-being, mental and physical health, and social relationships.

In the case of Extraversion, even though body motion patterns were identified, it was only Determinism when talking about their bodily perception and sensory life experiences, that led to more deterministic patterns. Conscientiousness was also connected to lower deterministic patterns regardless of the topic, which calls for further exploration in terms of the significance of Determinism in the context of personality traits.

Overall, this study exhibited the effect of high-level constraints (operationalized as three different self-referencing topics) on the dynamic self-organization of body motion dynamics, a reflection of sensorimotor processes. As mentioned in the discussion of Chapter 4, these findings align with the notion that individuals' personality traits are best understood when immersed in meaningful environments and different requirements of those environments can promote differences in flexibility and attunement with their immediate environment (Gallagher, 2013; Gallagher & Daly, 2018). Furthermore, participants reported less negative affect after completing the experimental task, suggesting that self-disclosure can improve mood, except for those with high levels of Neuroticism (low emotional stability).

Body motion dynamics reflect self-organizing processes indicative of underlying sensations, feelings, thoughts, memories, emotions, and meaning (Gallagher & Daly, 2018; Di Paolo, 2021). The high-level constraints likely created situations requiring individuals to adapt to changing environmental demands, a concept known as self-organized criticality (Goodwin, 2001; Plenz et al., 2021). Our results support earlier studies on the dynamic nature of human systems and their capacity for emergent self-organized behavior and critical states under specific conditions (e.g., Kelso & Schöner, 1988). Nevertheless, as a cautionary note, we interpreted the differences induced by situational constraints (topics) as shifts or transitions in the system's dynamics, such as critical states –i.e., variability between situations. However, such shifts or transitions would be more precisely visualized in the complete time series over time. This approach allows for identifying specific patterns, possible transitions in the systems' dynamics, and understanding the temporal context and sequence of events (data points) in which these changes occur. Therefore, this interpretation should be considered carefully in the context of our aggregated RQA measures across the three self-referencing topics. Consequently, should assess the continuous trajectories of these variables over time and across different situations/tasks to determine precisely when those transitions and shifts in the system's dynamics occur.

Temperament and self-organizing dynamics in infants

Intra-individual motor organization, as studied in Chapter 6, was connected to infants' temperament. The core idea was that temperament dimensions reflect individual differences in emotional and behavioral reactivity observed during infancy (Tang et al., 2020), which can manifest through changes in the dynamic organization of movements. This study was based on a mother-infant interaction, for which the infants' behavior was influenced by the mother. However, we focused on the infants' limb motor organization, following the aim of obtaining relevant insights into the coordination of elements of this developing motor system, intra-individual synchronization.

The positive relationship between Negative Affectivity (NEG) and both motor system complexity (Entropy) and stability (Mean Line) at 6 months of age was unexpected; as we initially anticipated that higher NEG would predict less organized and more unstable motor patterns. Instead, our data suggests that infants with higher NEG exhibit both more complex and more stable motor behaviors. In this regard, NEG encompasses reactive behaviors such as discomfort, fear, anger, and sadness (Rothbart & Bates, 2006; Olino et al., 2011). Infants with higher NEG are often characterized by frequent and intense limb movements and difficulties in sensory processing, which can indicate a less developed integration between perception and action (Gerardi-Caulton, 2000). These relationships were not observed at 12 months. Instead, the task context became more relevant, reflecting the developmental shift from less organized motor patterns to more synchronized and functional ones (Thelen & Smith, 1994). This aligns with the critical period for motor development at 12 months, characterized by exploration, object interaction, and the onset of walking (Adolph et al., 2015).

As discussed in Chapters 4 and 6, in the context of complex systems, Entropy is a measure of complex behavior, but it can also indicate unpredictability, irregularity, and chaos in a system's behavior when it is at high levels (Hirsh, 2012). Therefore, Entropy can be indicative of a complex and flexible system that can adapt to various stimuli; and, beyond an adaptive limit and without other variables such as stability and deterministic patterns, the system can become chaotic which may not be adaptive. Entropy, in the context of complex systems, can be understood as a measure of information, and quantifies the amount of uncertainty or unpredictability within a system (e.g., López-Ruiz et al., 1995). Higher Entropy can indicate greater complexity and less predictability, suggesting that the system has a rich informational content. This concept, derived from information theory, aligns with the idea that more complex systems can process and generate more information due to their numerous possible states and interactions.

For infants with high NEG, the increased Entropy might reflect a heightened level of motor activity and responsiveness to environmental stimuli. This could mean that these infants are continuously adjusting their motor behaviors which can be linked to behavioral reactivity, leading to a more entropic motor system. Stability, as measured by the Mean Line in our analysis, refers to the consistency and predictability of motor patterns. The finding that higher NEG is also linked to greater stability might seem counterintuitive. However, it can be explained by considering that these infants, despite their reactive behavior develop a consistent pattern in their motor responses. This could be due to the frequent practice and repetition of movements driven by their high reactivity, which over time leads to more stable motor patterns. Therefore, this high level of engagement and reactivity may propel both complexity (through increased motor activity and adaptation) and stability (through repetition and practice of movements), thus resulting in a motor system that is both highly active and consistently organized. These findings align with previous research indicating that NEG is associated with extensive limb movements and a need for greater sensory processing (Sallquist et al., 2009; Cioffi et al., 2021). It is relevant to further investigate whether these dynamics can underlie a complex mechanism that is functional to the developing system.

Furthermore, a longitudinal finding was that NEG at 6 months continued to be linked with Entropy at 12 months, indicating a persistent effect on motor system development. Additionally, maternal anxiety (measured as a trait) was negatively related to both Entropy and Mean Line at 12 months, evidencing a connection between children's motor development and maternal psychological characteristics (Bornstein, 2002; Wittig & Rodriguez, 2019). In this case, as anticipated, maternal anxiety was linked to decreased complexity (Entropy) and stability. These results are relevant because they suggest that Entropy might reflect different self-organizing processes at various developmental stages (different within infancy and in adulthood). Moreover, maternal anxiety can be also exacerbated as a reaction to the infant's vulnerability, which can emerge as a reinforcing feedback loop where the maternal anxiety and infant reactivity are circularly interacting. Fundamentally, future studies must examine the interaction between relevant dynamic measures over time, such as Entropy, Mean Line, and Determinism (deterministic patterns) to comprehensively understand the dynamics and mechanisms expressed in these measures and how they reflect the behavioral patterns that constitute temperament in infancy. In addition, it is fundamental to explore what are the "optimal" thresholds for Entropy to be characterized as complex adaptive behavior and chaotic behavior, which may be a rather fluid continuous that also depends on the interaction with other systems characteristics such as stability, deterministic patterns, attractor strength, among others.

Throughout all studies of this dissertation, the connection between embodied dynamics with personality and temperament was evidenced and provided meaningful insights, in the latter case, as evidence of the dynamic interplay between temperament and motor development. In the next section, I will discuss the techniques employed in this dissertation, especially examining their benefits, limitations, and future directions.

Methodological Insights

Time series analyses

The techniques employed to operationalize synchronization provided relevant insights in the context of this dissertation. I mainly used linear and nonlinear time series techniques to quantify body motion and speech dynamics. In Chapter 3, to quantify interpersonal synchronization and dynamic organization of body motion, the techniques utilized were Windowed Lagged Cross-Correlations (WLCC) (linear) and Cross-Recurrence Quantification Analysis (CRQA) (nonlinear). As mentioned before, WLCC is a statistical technique used to measure lagged correlations between two time series (Schoenherr et al., 2019), in this thesis, body motion time series extracted from Motion Energy Analysis (MEA, Ramseyer, 2020). In the case of this thesis, We utilized a grand average to quantify the overall strength of interpersonal synchronization. There are several considerations to keep in mind when using a technique that uses cross-lagged correlations: The most logical is choosing wisely the correct lag and other parameters that accurately reflect the process we aim to measure while being appropriate for the time series we are working with.

We employed the parameters suggested for WLCC using MEA (Motion Energy Analysis) (lag = 5 seconds, window = 30 seconds, increment = 10 seconds) (Kleinbub & Ramseyer, 2020). The 5-second lag captured how the two time series influence each other with delays of up to 5 seconds. The 30-second window size balanced the need for reliable correlation estimates while maintaining temporal resolution. The 10-second increment shifted the sliding window by 10 seconds each time, creating overlapping windows that ensure smooth and continuous changes in the correlation over time, avoiding abrupt transitions (Kleinbub & Ramseyer, 2020). A limitation of this thesis is that I did not test different parameters in this type of analysis, which might have resulted in more detailed and perhaps different results for different dyad compositions, as some individuals might be attuned to very short or longer behavioral cues; or may exhibit different response latency. In this sense, it might be desirable to test different parameters based on the literature, and perhaps compare what type of processes can be captured by each set of parameters.

In Chapter 3 we incorporated CRQA alongside WLCC as it offers a set of robust nonlinear time-series measures suitable for examining complex dynamical systems. CRQA effectively captures the subtle patterns of synchronization through short-range and long-range coupling in the behavior of two systems, extending recurrence analysis to two time-series from the same or different systems (Wallot & Leonardi, 2018). This aligns with the importance of global matching of complexity properties occurring at different timescales, at different delays, and across the whole interaction (Delignières & Marmelat, 2013). This method allowed us to extract synchronization patterns that might be missed by linear techniques alone, providing a comprehensive understanding of the dynamic organization of body motion. In this sense, even though we extracted a single value per variable (i.e., Determinism, Entropy, Laminarity, Mean Line), the calculation of each of these variables considers the synchronization at different time scales. This adds measures of global matching among the dyads. The parameters we chose for this analysis were based on the advised procedures in the literature (e.g., Wallot & Leonardi, 2018): The phase state reconstruction parameters were set to a lag = 40 and an embedding dimension of 7, lmin = 2 (default). To determine the dimensionality of our phase space, we calculated the average mutual information for estimating the delay, considering the first local minimum as a good estimate (Abarbanel, 1996; Wallot & Leonardi, 2018). The false-nearest-neighbor procedure was used to estimate embedding parameters, again searching for the first local minimum (Kennel et al., 1992). This ensures the selection of the necessary surrogate dimensions to unfold the attractor dynamics reliably (Wallot & Leonardi, 2018).

In Chapter 4, Recurrence Quantification Analysis was performed as a nonlinear technique to measure the recurrence states of a system (Marwan et al., 2007), based on body motion time series. This approach followed the argument of CRQA, aiming to capture properties of self-organizing dynamics that occur at different time scales and delays. In this case, since the time-series were the same kind as in Chapter 3, but only at the individual level, we preserved most of the parameters set before, except for minimum line length (lmin). The minimum line length defines the shortest diagonal line considered in the analysis (Zbilut & Webber, 2006). In our study, we set lmin to four consecutive recurrences (lmin = 4), meaning that deterministic patterns must last at least 120 milliseconds (0.12 s), similar to previous studies (Tommasini et al., 2022). While the default value in the literature is 2, we opted for a conservative setting to reduce the inclusion of relatively small and random diagonal lines (Cox & Van Klaveren, 2024; Thiel et al., 2002; Tommasini et al., 2022; Sviridova & Ikeguchi, 2022). In this sense, again, it would be possible to test different parameters for different systems and whether those changes would lead to different outcomes. However, these choices worked appropriately in providing meaningful results, and in detecting interesting differences in the global behavioral patterns.

In Chapter 5 the methodological approach was based on categorical speech time series (speech and silence) and we employed extensions of the traditional CRQA: Categorical CRQA to assess speech synchronization given the type of time series (at lag zero, RR_{LOS}; and global RR_{global}), Diagonal Cross-Recurrence Profiles (DCRP) to assess leading-following dynamics (QDCRP), and Anisotropic CRQA, to measure the nonverbal interactional dominance (through LAM_{ARD}, and TT_{ARD}). In these types of categorical analysis, the parameters are more standard because of the categorical time series we worked with, in which case, we used default settings. Categorical CRQA focuses on the patterns and recurrence of discrete states, which do not require the same level of parameter sensitivity as continuous data. The default parameters (embedding dimension = 1, delay = 1, radius = 0) effectively capture the recurrence patterns in categorical sequences (Cox et al., 2016, Wallot & Leonardi, 2018). A strength of this study was the variety of measures we extracted to assess speech synchronization and the leading-following dynamics and nonverbal interactional dominance within dyadic interactions, which provided a very detailed level of analysis in connection with personality and interaction appraisals.

As a methodological insight, one of the most relevant parameters to consider is the time-lag because it defines the shortest time (i.e. the smallest timescale) at which the behavior of the interactants will be considered to be related (Scheidt et al., 2021). The primary focus of time-lag is on the timing of behaviors, examining how behaviors align over different time scales. It determines the smallest timescale at which the behavior of interactants is considered related. There are some considerations concerning time-lag and the process of synchronization to be captured, as it can be differentiated into three categories (Altmann, 2013; c.f., Scheidt et al., 2021): 1. No time-lag indicates simultaneous behavior, as reflected in Chapter 5 by the categorical CRQA, particularly through speech synchronization at lag-zero or RR_{LOS}. Also, this was captured in Chapter 3 but a range of synchronized behaviors ranging from simultaneous to delayed by the variable of synchronization strength, and by the Diagonal Cross-Recurrence Profiles using Q_{DCRP} when there is no delay. 2. Synchronous behavior with time delay (time-lag) which reflects alignment but not simultaneous, as reflected in Chapter 3 by synchronization strength and Chapter 5 by global speech synchronization (RR_{LOS}), and employing Diagonal Cross-Recurrence Profiles utilizing Q_{DCRP} when there is delay. 3. Convergence and adaptability, or similarity increase across time, indicates how interacting elements or systems become more similar or coherent in their behavior over time, describing an adaptive or convergent process. This was captured generally through various techniques across chapters, particularly through the plots of each technique.

In Chapter 3, the WLCC and CRQA informed about the convergence and adaptability of the behavior of both interacting partners, visually, it was possible to assess whether the similarity of body motion increased over time (more convergence) and if one person adapted to the other (i.e., one person displayed a behavior and was followed by the partner after some delay) (e.g., Figure 1, panel A). However, the transitions over time were only possible to visualize in the plots of each dyad, not in the aggregated measures that were extracted (synchronization strength and CRQA measures). Similarly, in Chapter 5, convergence and adaptability were visible in the DCRPs, where the speech turns inform about leader-follower behaviors by lags, representing a form of adaptability over time. In the DCRPs, the line of synchrony (LOS), corresponds to lag zero, and the lags to the sides of the line of synchrony line indicate that one behavior (i.e., speaking) was leading, and the other behavior (i.e., listening) followed after a certain time delay. This indicates a temporal pattern where one person initiates a turn, and the other responds after a specific duration, suggesting a form of convergence and adaptability (see Figure 1, panel C, or Chapter 5).

Furthermore, while the temporal aspect is crucial, the content of the interaction can also influence synchronization, as elaborated throughout this dissertation. The type of interaction, the context, and the specific behaviors or responses being measured can affect how and when synchronization occurs. In this sense, both the content of interactions and their timing play roles in synchronization. Time-lag focuses on when behaviors align, while the content provides context for understanding why and how these behaviors synchronize.

Design of the studies: The experimental situations

In addition to the methodological insights regarding the time series analyses, it is relevant to briefly delineate the relevance of the experimental situations employed in this dissertation, with emphasis on the laboratory setup, design choices, and other methodological considerations.

The laboratory studies of Chapters 3, 4, and 5, were designed to investigate how personality traits are expressed in body motion in individual and interpersonal settings. In the dyadic task, the goal was to maximize the effects of the personality traits of each interacting partner to capture such effects in short interactions. For this reason, we decided to conform dyads either similar or dissimilar in the socially relevant traits of Extraversion and Agreeableness, following a similar procedure as the one reported by Cuperman & Ickes (2009). We set a threshold of 0.5 SD above or below the group average to determine if a personality trait's level was "high" or "low" (following Li et al., 2020). In this sense, we found significant effects of personality traits on interpersonal synchronization and relevant insights regarding different dyadic compositions, such as the role of Extroversion in mixed extrovert and introvert dyads. However, it would be interesting to test a less simplistic approach that considers a more comprehensive approach such as a dynamic approach to personality (taking into consideration the variability of each trait over time), or personality profiles instead of focusing on single dimensions –in this case, Extraversion and Agreeableness. For instance, Neuroticism might be a relevant dimension to consider in interaction with others such as Extraversion and Conscientiousness, as reported by previous studies (Li et al., 2020). We indeed observed that Neuroticism and Conscientiousness were expressed in body motion in individual settings when participants were talking about themselves (Chapter 4), for which it would be relevant to test the role of these and other traits (personality x personality interactions) in interpersonal synchronization. And, we further found a small effect of Openness to experience in the individual task which became nonsignificant after correcting the p-values, which would be a call for testing such body motion dynamics in a larger sample. It is important to consider that an approach that considers all personality dimensions in interpersonal settings would involve a much larger sample size, which becomes challenging in experimental studies.

Regarding the structure of the dyadic and individual tasks, we considered three types of conversations with the same duration in both cases: a full conversation of 15 minutes and 5 minutes per topic. This setup allowed for a structured yet flexible exploration of how different high-level constraints (topics) might influence body motion dynamics at individual and interpersonal levels. In both cases, the length of each topic was enough to see different effects on interpersonal synchronization and self-organizing dynamics respectively.

Strengths, Limitations, and Future Directions

As follows from the previous paragraphs, the parameter setting is a fundamental aspect of time-series analysis. An insight I could obtain by developing this thesis is that it needs careful assessment, and more work needs to be done to ensure that we are choosing the parameters according to our data and the processes we would like to assess. Further studies comparing the effects of different settings in diverse time series would be insightful to develop a clear research protocol in the field of synchronization. For example, it is not the same to assess interpersonal synchronization of body motion as interpersonal synchronization of skin response, brain oscillation, or cognitive processes (Schoenherr et al., 2019; Scheidt et al., 2021). As detailed in Schoenherr et al. (2019), research on skin conductance found meaningful synchronization was found at a maximum lag of 7 seconds (Robinson et al., 1982), whereas other researchers recommend time-lag from 0.04 to 4 seconds for motor mimicry (Bilakhia et al., 2015). Other researchers have opted for 5 seconds to assess nonverbal synchronization (Tschacher et al., 2020). One further approach might be to evaluate the best time-lag based on the comparison with shuffled data, suggesting that this choice can be determined empirically (Schoenherr et al., 2019). Schoenherr et al. (2019) demonstrated that different time series techniques capture various facets of nonverbal synchronization in body motion, such as the overall strength of synchronization, the strength during specific intervals, and the frequency of synchronization events. This further calls for caution when designing our studies, and, from my perspective, implies a strength in this thesis by defining multiple variables and facets of synchronization or dynamic organization throughout the studies developed. Overall, the choice of each of the parameter values that are involved in the time-series analyses requires deep assessment, for interested readers, the information provided by Schoenherr et al. (2019), Scheidt et al. (2021), Wallot & Leonardi (2018), and Kleinbub & Ramseyer (2020) can be helpful.

While our research employed robust and innovative methodologies such as RQA, CRQA, WLCC, and MdRQA, there are limitations to consider. The sample sizes, particularly for the infant study (Chapter 6), were relatively small, which may limit the generalizability of the findings. Future research should aim to replicate these studies with larger, more diverse samples. However, all the experimental studies of this thesis involved collecting data in a laboratory, which adds richness to the data and also the downside of having a limited sample. And, regardless of the sample, we were able to find meaningful results that can be useful for future research.

As a second limitation, I can say that using single aggregated variables could have restricted the identification of specific transitions along the time series within each topic –if they occurred, preventing from capturing specific shifts and critical states in very short time scales (e.g., milliseconds/seconds). However, this approach was chosen given the next modeling step with the variables of personality, temperament, and appraisals, for which having single variables to model was adequate. Moreover, as mentioned before, the robustness of the nonlinear techniques ensures capturing dynamics through the whole time series, and the downside of not seeing the patterns continuously was compensated by having different high-level constraints (topics) to compare variations in behavior among very different situations. And, the idea of having different conversational or self-referencing topics was meant to amplify any differences in behavior that could be observed. In the future it would be advised to include a time series approach such as windowed cross-lagged correlation (Watanabe, 1983) (similar to WLCC, but as a nonlinear version), preserving the continuous integrity of the data. And, as a modeling approach, it would be recommended to utilize one that supports continuous data such as Generalized Additive Mixed Models (GAMM, e.g., Wieling, 2018). This is a statistical modeling approach to analyze dynamic patterns which allows for nonlinear relationships between the variables by fitting a smooth function for each predictor variable while allowing for random effects (which accounts for effects outside of the variables within the model) (Wieling, 2018).

Third, while our techniques are powerful for capturing complex dynamics, they require careful implementation and interpretation. This is true especially for variables such as Entropy, which is a very interesting variable, but can be challenging to interpret compared to more straightforward measures like Determinism (which indicates deterministic patterns) or Mean Line (which indicates stability). In the context of personality and psychological science, high Entropy might signify a varied behavioral repertoire, allowing for adaptability and flexibility in changing environments. Importantly, Entropy can indicate phase transitions in the systems' dynamics when moving to new states (or metastable states) (e.g., Olthof et al., 2020). Therefore, interpreting Entropy requires a comprehensive understanding of the underlying mechanisms and dynamics, as it encompasses a broader range of possibilities, including both adaptive behavior and potential disorganization or chaos. In the realm of personality research, chaotic dynamics can suggest that what might seem like random fluctuations in behavior could actually be the result of complex, deterministic processes (Guastello & Liebovitch, 2009; Den Hartigh et al., 2017). This challenges traditional views on behavioral randomness, proposing instead that apparent randomness may mask underlying deterministic structures. Moreover, the presence of chaos as part of complex adaptive systems underscores the importance of temporal dynamics measurement and the difficulty of making long-term predictions. In this sense, researchers should continue to refine these methods and explore their applications in different contexts, time scales, and psychological or interpersonal processes.

Fourth, while the findings shown throughout this dissertation are promising, it is essential to recognize that the observed effects are often small or emerge within the context of complex interaction effects. These effect sizes, which quantify the magnitude of the relationships, are integral to understanding the implications of our results. In the realm of complex systems, such as those represented by human behavior and personality, small effect sizes do not necessarily imply weak or inconsequential associations. In the case of this thesis, they reflect the subtle, complex ways in which an individual's embodied dynamics synchronize with others or manifest during tasks. These small but consistent effects are critical, especially in clinical contexts, where such nuances might reveal significant aspects of how individual behaviors emerge and coalesce into patterns perceived as personality traits. Fundamentally, these patterns are not isolated phenomena but part of broader self-organizing systems that unfold over time and across different contexts, and for this reason, it is not uncommon to find small or medium effect sizes (e.g., Galbusera et al., 2019; Jiang et al., 2023; Macpherson et al., 2024). The ability of recurrence-based techniques to detect and analyze these subtle effect sizes underscores their utility. In real-life interactions, it is often these minor, almost imperceptible dynamics that individuals pre-reflectively perceive and respond to, shaping their perceptions and interactions. In this sense, effect sizes can also be impacted by the type of modality assessed, the number of data points in the time series, and the modeling approach. However, the results in this thesis reflect the need to conduct further research with larger samples, additional modalities of behavioral and physiological measurements, and different types of situational constraints.

Future research should build on our findings by exploring additional factors that influence synchronization in adults and motor system organization in infants. For instance, investigating the role of other personality traits in interpersonal synchronization such as Neuroticism, Conscientiousness, and Openness to experience, could further enrich the understanding of how the traits of each partner affect synchronization and interactional appraisals. Additionally, expanding the participant pool to include more diverse demographics could enhance the generalizability of the findings. Longitudinal studies could provide deeper information into how these dynamics evolve over time and in response to interventions. Furthermore, multimodal layers of data can provide accurate information about the systems' dynamics, which can be further incorporated into machine learning as well as (causal) dynamical models to identify and predict patterns associated with psychological traits and psychopathological conditions (e.g., depression, anxiety).

Theoretical and Practical Implications

The research developed in this dissertation has several theoretical implications. First, it supports enactive, embodied, and complex dynamical systems theories by demonstrating how personality and temperament are expressed through dynamic bodily and speech patterns. This underlines the importance of considering the body and environment coupling in psychological theories. Second, the findings contribute to complex systems theory in the following ways: Through the theoretical standpoint by which the studies were developed, approaching individuals, their behavior, and their personality traits as complex dynamical systems. And, through the methods employed in all the experimental studies, it was possible to extract meaningful patterns, as well as identify emergent properties of interpersonal and intra-individual dynamics such as the emergence of interpersonal synchronization (in Chapters 3 and 5) and self-organizing dynamics (in Chapters 4 and 6). These insights suggest that personality and temperament can be understood as dynamic, self-organizing, and embodied systems influenced by the coupling between individual and environmental elements. These insights can have impacts on personality psychology, especially, in future experimental studies by integrating self-report measures with direct measures of behavioral patterns.

In clinical psychology, understanding body motion dynamics (e.g., synchronization and self-organizing dynamics) can inform about psychopathological conditions, social skills, and the quality of the therapeutic alliance (e.g., rapport as proposed by Ramseyer, 2020). The task and measurement procedure used in this thesis, involving conversations, self-referencing tasks, and the analysis of body motion dynamics, present a promising tool for clinical assessment. This approach is both easy to implement and cost-effective, making it suitable for integration into clinical practice.

The procedure of having individuals speak about themselves or with someone else on specific topics while their body motion is analyzed could be adapted for clinical settings. Particularly, the non-invasive nature of the task and the straightforward setup (a camera and analytical software) make it feasible for routine use in clinical settings, such as the screening of psychopathologies. Embodied dynamics such as movement and facial synchronization can be implemented in the diagnostic process for psychopathological conditions like depression by identifying patterns associated with mental health conditions (e.g., Altmann et al., 2021). For example, individuals with depression might exhibit less dynamic and more rigid body movements, while those with anxiety might show erratic and unstable motion patterns, in line with research on the so-called embodied affectivity (Fuchs & Koch, 2014).

Furthermore, one of the insights of our results is that using complex systems techniques can be expanded to any modality of assessment that can create time series, either continuous (e.g., body motion, heart rate, galvanic skin response, or EEG) or categorical (e.g., behavioral coding). For instance, categorical RQA has proven to be effective in finding dynamic patterns in expressive writing associated with depression

(Lyby et al., 2019). Overall, a methodological approach like the one presented in this thesis can complement traditional assessment tools by providing observable data on how personality traits or psychopathological conditions manifest in embodied patterns. This could be particularly useful in cases where self-report measures might be biased or inaccurate. In light of our results, clinicians could use body motion dynamics to monitor improvements in emotional stability, or reductions in anxiety, which could be reflected in more organized and stable motion patterns (e.g., expressed in higher Determinism and Mean Line). Similarly, time series analysis can be used in biofeedback interventions by providing patients with real-time feedback on their behavioral patterns, which could help them develop greater body awareness and potentially improve emotional regulation.

In developmental psychology, our results delineate the importance of supporting the caregiver's well-being and mental health, which can impact caregiver-infant interactions to promote healthy motor and emotional development. Tracking infants' body motion dynamics and interpersonal synchronization can provide insightful information about developmental trajectories beyond the motor aspect, expanding to dimensions such as emotional regulation (or Negative Emotionality). Mental health programs designed to reduce maternal anxiety could have beneficial effects on infant motor system organization during the first year of life.

Conclusion

This thesis has advanced our understanding of the dynamic interplay between embodied dynamics, environmental constraints, and psychological traits. By integrating enactive, embodied, and complex systems perspectives, we have shown how personality and temperament are linked to synchronization processes and motor system organization. As elaborated throughout the different chapters, this thesis followed an attempt to promote an integrative theoretical framework while testing the principles in experimental settings. This was partially accomplished, and as the reader might have noticed, while the first theoretical chapter was ambitious, there are still many elements that I was not able to cover in the studies presented. For instance, exploring closely how the selective engagement with multiple affordances can be studied in experimental or ecological settings, including more extensive measurements (e.g., longitudinal), and the incorporation of multiple modalities in an integral analysis, just to mention some. Yet, the work contained in this thesis offers relevant results and implications for future research. The key contributions of this dissertation include:

Integration of Theoretical Frameworks: This thesis offers an integrative framework for comprehending the dynamic interplay between individuals and their environments, presenting a comprehensive and coherent perspective on personality expression. This framework incentivize viewing personality as an emergent property arising from ongoing interactions between embodied individuals and their surroundings, which has the potential to be expanded to other psychological phenomena.

Implications for Personality Theory: The findings encourage a more fluid, embodied, situated, reciprocal, soft-assembled, emergent, and interactionist approach to studying individual differences. It encourages to explore how embodied individuals engage with multiple affordances and enact their environments. This perspective promotes a focus centered in dynamic interaction patterns and stylistic differences in the way of perceiving and engaging with the world.

Novel Methodological Approaches: By employing time-series analysis techniques, such as various forms of Recurrence Quantification Analysis (RQA), this thesis provides a detailed examination of body motion and speech synchronization. These techniques reveal patterns in brief glimpses of behavior related to personality traits, offering new ways to quantify and analyze complex human dynamics.

Extension to Infant Development: The research extends to infant development, exploring the developmental roots of motor system organization and its connection to temperament. This emphasizes the inseparable link between early embodied dynamics, psychological traits, and maternal mental health, offering insights into the foundational aspects of human development.

Methodological Insights and Limitations: The use of time-series analysis has certain limitations, such as setting the proper parameters according to the processes to be assessed and the modality of data. This encourages researchers to continue developing experimental studies, applying, and refining such approaches.

Practical Applications and Implications in Research: Insights from this research could inform interventions and be incorporated into diagnostic tools by focusing on the role of embodied dynamics in expressing personality and psychopathological conditions. Utilizing non-invasive assessment methods such as the ones presented in the thesis, together with technology such as wearable sensors and machine learning techniques, it is possible to capture dynamic patterns in diverse modalities and analyze them with greater precision in real-world settings.

Overall, this dissertation lays a robust foundation for future research, providing both theoretical and practical insights. It advocates for the incorporation of nonlinear dynamics and innovative methodologies alongside traditional techniques to enhance our understanding of human behavior and development. By embracing enactive, embodied, and dynamic perspectives, future research can further investigate the complexities of human behavior, leading to more effective interventions and a deeper comprehension of personality, temperament, and psychological phenomena. Importantly, this dissertation underscores the vast potential for continued investigation and development in this field, indicating that there remains substantial work to be done to comprehend, expand upon and apply these insights in practice.

Chapter 8

Nederlandse Samenvatting

Een Complex Dynamische Benadering van Persoonlijkheids- en Interpersoonlijke Dynamiek: Integratie van ‘enactive’ en Belichaamde Perspectieven

Er is een fundamentele koppeling tussen individuen als belichaamde 'agents' en hun omgeving, die ook wordt gevormd door andere individuen (Varela et al. 1991; Johnson 2015; Di Paolo 2021; Nowak et al. 2020). Deze omgeving biedt mogelijkheden voor actie, waarbij individu en omgeving zijn gekoppeld door wederkerige maar niet altijd symmetrische interacties. Dit wordt ook wel wederkerige causaliteit (Thompson & Varela 2001) of circulaire causaliteit (Fuchs 2020) genoemd. Ons lichaam verbindt ons organisch met onze directe omgeving. Dit betekent dat de psychologie als wetenschap dimensies zoals belichaming, omgevingscontext en intersubjectiviteit moet omvatten om de geest volledig te kunnen begrijpen (Thompson 2007).

Binnen dit landschap past de persoonlijkheidstheorie, die een kader biedt om te begrijpen hoe individuen zich gedragen, interacteren, beoordelen en hun wereld vormgeven. Persoonlijkheid is cruciaal voor het begrijpen van interacties tussen individuen en hun omgeving en is essentieel binnen een complex dynamisch, 'enactive' en belichaamd perspectief (zie verderop). Persoonlijkheid is een dynamisch onderdeel van een breder systeem dat zich verder uitstrekt dan het individu alleen. Daarom moeten de patronen en stilistische verschillen die de persoonlijkheid vormen, gezien worden als integrale componenten van complexe adaptieve systemen. Dit suggereert dat traditionele manieren van persoonlijkheidsmeting (zoals zelfrapportage vragenlijsten) de dynamische eigenschappen van persoonlijkheid, zoals die zich manifesteren door belichaamde interacties en dynamische betrokkenheid met de wereld, zouden moeten omvatten.

Deze dissertatie rapporteert over een onderzoeksproject naar de relatie tussen psychologische eigenschappen, met name de uitdrukking van persoonlijkheid bij volwassenen, en de dynamiek van hun lichaamsbeweging en synchronisatie van spraak. Het laatste hoofdstuk breidt deze studies uit naar het temperament van baby's en de relatie daarvan met de bewegingsdynamiek van hun ledematen om de verbinding tussen belichaamde dynamiek en psychologische eigenschappen te verduidelijken. Alle hoofdstukken integreren een complex dynamisch, 'enactive', en belichaamd perspectief.

Enactive, Belichaamde en Complexe Systeem Benaderingen in de Psychologische Literatuur: Concepten behandeld in deze dissertatie

Deze dissertatie maakt gebruik van de 'enactive', belichaamde en complexe dynamische systeem benaderingen. De ***enactive theorie*** beschrijft hoe individuen hun ervaringen vormgeven door voortdurende interacties met hun omgeving, waarbij een complex adaptief individu-omgeving systeem ontstaat (Thompson & Varela 2001; Thompson 2007). ***Belichaming*** is fundamenteel omdat een belichaamde geest de toestand van het hele organisme weerspiegelt en integreert (Varela et al. 1991; Gallagher 2018; Fuchs 2020).

De belichaamde cognitie (embodied cognition) ziet individuen als dynamische systemen waarbij variabelen continu en onderling afhankelijk van elkaar veranderen volgens dynamische wetten (Chemero 2009). Het kader van de ***complex dynamische systemen (CDS)*** biedt methoden om niet-lineaire dynamiek en belichaamde interacties binnen een complex adaptief systeem te bestuderen, wat leidt tot opkomende eigenschappen en gedragspatronen (Thompson & Varela 2001; Richardson & Chemero 2014).

Deze inzichten kunnen worden uitgebreid naar de studie van ***persoonlijkheid*** door te onderzoeken hoe persoonlijkheid wordt uitgedrukt in daadwerkelijk gedrag (i.h.b. bewegingen) van het individu en contextuele interacties (Richardson et al. 2014). De 'enactive' benadering stelt dat gedragspatronen en persoonlijkheid voortkomen uit de interactie tussen individu en omgeving in een wederkerige causaliteit (Thompson & Varela 2001; Hovhannisyan & Vervaeke 2022; Satchell et al. 2021). De belichaamde benadering benadrukt het belang van het lichaam in het vormgeven van ervaring en gedrag, en suggereert dat persoonlijkheidskenmerken diep verstrengeld zijn met onze fysieke constitutie en bewegingen (Koppensteiner 2011; Jiang et al. 2023). Het CDS kader stelt ons in staat persoonlijkheid te bestuderen als onderdeel van een dynamisch systeem waarin uit meerdere gekoppelde componenten algemene eigenschappen emergeren die niet volledig kunnen worden begrepen door elke component afzonderlijk te onderzoeken (Fajkowska 2015; Nowak et al. 2020; Michaels et al. 2021).

Synchronisatie is een fundamenteel mechanisme voor het begrijpen van menselijk functioneren, inclusief de dynamiek van gekoppelde componenten in complexe systemen (Vallacher et al. 2002; Nowak et al. 2020). Mensen synchroniseren hun gedrag als reactie op omgevings- en intra-individuele factoren (Nowak et al. 2020). Dit model verklaart hoe coherente functionele eenheden ontstaan door de synchronisatie van lagere niveau elementen in hersenen, geest en sociale systemen (Nowak et al. 2017, 2020). In deze dissertatie richt ik me specifiek op de synchronisatie van lichaamsbeweging en spraak en hoe die gekoppeld zijn aan kenmerken van persoonlijkheid. De relatie tussen synchronisatie en persoonlijkheid is bidirectioneel en wordt gestuurd door circulaire causaliteit (Fuchs 2020; Nowak et al. 2020), wat betekent dat synchronisatie de expressie van persoonlijkheid beïnvloedt en nieuwe eigenschappen in interacties kan bevorderen (Nowak et al. 2020). Meer hierover wordt behandeld in de verschillende hoofdstukken van deze dissertatie.

Deze benadering helpt ons de vloeiende en adaptieve kwaliteiten van persoonlijkheid te begrijpen, met name door de manifestatie ervan door belichaamde dynamiek op intra-individueel en interpersoonlijk niveau, de interacties met de wereld, en de functionele synchronisatie die deze processen ondersteunt. De centrale onderzoeksvraag in deze dissertatie is als volgt geformuleerd: *Hoe weerspiegelen de dynamiek van lichaamsbewegingen en spraakpatronen de wisselwerking tussen persoonlijkheidskenmerken, temperament, interpersoonlijke synchronisatie en omgevingsinteracties?*

In deze dissertatie

Hoofdstuk 2 biedt een fundamenteel kader en integreert 'enactive', belichaamde en complexe systeem perspectieven in de persoonlijkheidsleer, met nadruk op de onderlinge verbondenheid van organismen en de omgeving. Dit belicht de verbinding tussen persoonlijkheid en de theorie van ***affordances*** (d.w.z. concrete handelingsmogelijkheden voor een individu aanwezig in de omgeving). De daarop volgende drie empirische hoofdstukken verkennen de expressie van persoonlijkheid bij volwassenen, interpersoonlijke en intra-individuele synchronisatie door middel van lichaamsbeweging ***(Hoofdstukken 3 en 4)*** en synchronisatie van spraak ***(Hoofdstuk 5). Hoofdstuk 6*** breidt de eerdere benaderingen uit naar baby's en onderzoekt de relatie tussen de organisatie van het motorische systeem, temperament en 'maternal anxiety' op 6 en 12 maanden leeftijd.

Hoofdstuk 2: Integratieve perspectieven op 'enactive', belichaamde en complexe systemen toegepast op persoonlijkheidsleer

Dit hoofdstuk biedt een theoretische basis, die de belangrijkste onderwerpen van deze dissertatie en enkele daarbuiten omvat. Persoonlijkheidskenmerken worden gedefinieerd als individuele verschillen in gedragspatronen, affectie, cognitie en verlangen die ontstaan in de interactie met de omgeving waarin individuen zich bevinden (Wilt & Revelle, 2019; Satchell et al., 2021). Persoonlijkheid wordt verder beschouwd als een dynamisch construct dat nauw verbonden is met de interactie met affordances, en reflecteert tendensen om de wereld optimaal te begrijpen (Hovhannisyan & Vervaeke, 2022), waarvoor de 'enactive' en complexe dynamische systeem perspectieven een betekenisvol kader bieden.

Het hoofdstuk begint met het integreren van 'enactive', belichaamde en complexe dynamische systeemtheorieën in een verenigd perspectief. Het onderzoekt hoe de complexe dynamische systeemtheorie bijdraagt aan de studie van persoonlijkheid door dynamieken op verschillende niveaus te bestuderen, inclusief intra-individuele en interpersoonlijke niveaus. Het concept van functionele synchronisatie wordt op deze niveaus geïntroduceerd. Het hoofdstuk pleit voor een uitgebreid kader dat verschillende dimensies omvat, zoals belichaamde, dynamische, zelforganiserende en intersubjectieve aspecten. Het bevat ook het skilled intentionality framework, geworteld in het veld van relevante affordances (Rietveld et al., 2018), en suggereert dat persoonlijkheidstrekken de interactie van een individu met affordances en sensorimotorische processen beïnvloeden.

Hoofdstuk 3: De interactiepartner als de directe omgeving: Persoonlijkheid en interpersoonlijke dynamiek

Het is bekend dat mensen in sociale interacties de neiging hebben hun lichaamsbewegingen vrijwillig en onvrijwillig te synchroniseren, wat veel individuele verschillen uitdrukt en de beoordeling van interacties kan beïnvloeden. Voortbouwend op een deel van de basis die in het vorige hoofdstuk is uitgewerkt, maakt Hoofdstuk 3 de overgang van theorie naar experimenteel onderzoek. Het richt zich specifiek op de rol van de persoonlijkheidskenmerken Extraversie en Aangenaamheid (sociale kenmerken) bij het ontstaan van interpersoonlijke synchronisatie en de dynamische organisatie van lichaamsbewegingen in dyadische interacties. Voor dit doel voerden jongvolwassenen een gesprek over drie onderwerpen: 1) introductie, 2) zelfonthulling, en 3) argumentatief. Beoordelingen van de deelnemers na afloop van de interactie werden onderzocht in de vorm van interpersoonlijke nabijheid, affectie en plezier als een manier van intersubjectieve uitkomsten. Wat betreft de gebruikte technieken, werd lichaamsbeweging gekwantificeerd met behulp van Motion Energy Analysis (MEA), een beeld-voor-beeld substratiemethode om de hoeveelheid lichaamsbeweging te meten. De interpersoonlijke synchronisatie werd verder onderzocht met verschillende vormen van tijdreeksanalyses. Dit omvatte het bepalen van synchronisatie sterkte en de dynamische organisatie.

De resultaten toonden aan dat Extraversie en Aangenaamheid een significante rol spelen in interpersoonlijke synchronisatie. Hoge Extraversie leidde tot sterkere synchronisatie en positieve beoordelingen van de interactie. Dyades met vergelijkbare Extraversie-scores hadden sterkere synchronisatie, vooral tijdens zelfonthulling. Gemengde koppels vertoonden stabiele koppelingen tijdens argumentatie. Aangenaamheid hing samen met hogere complexiteit van de interactie en entropie, en minder negatieve gevoelens na de interactie. Aangename individuen waren flexibeler en responsiever, wat leidde tot boeiende en aanpasbare interacties, terwijl minder aangename individuen meer rigide gedrag vertoonden.

Hoofdstuk 4: Persoonlijkheidsexpressie in de dynamiek van lichaamsbeweging: Een enactive, belichaamd en complexe systeem perspectief

In navolging van het thema van het vorige hoofdstuk, om persoonlijkheidsexpressie in de dynamiek van lichaamsbeweging op intra-individueel niveau te verkennen, onderzoeken we in Hoofdstuk 4 de verbinding tussen de dynamiek van lichaamsbeweging en verschillen in persoonlijkheid (Big Five dimensies). Hiervoor voltooiden jongvolwassenen een taak van 15 minuten die drie zelfreferentiële onderwerpen omvatte: 1) introductie, 2) lichaamsperceptie en sensorisch leven, en 3) socio-emotioneel leven. De dynamiek van lichaamsbeweging werd geëxtraheerd uit video-opnamen met behulp van dezelfde beeld-voor-beeld substratiemethode, Motion Energy Analysis (MEA, Ramseyer, 2020), als in de eerdere studie. Hierbij werd gebruikgemaakt van een niet-lineaire tijdreeksanalyse. Affectieve toestand werd opgenomen om te evalueren hoe de deelnemers de taak beoordeelden en ervoeren. Multilevel modellen schatten persoonlijkheid (Big Five domeinen/dimensies) en situationele effecten.

De resultaten toonden aan dat Neuroticisme voorspelde een minder deterministische en meer fluctuerende dynamiek, wat wijst op minder stabiele en meer variabele lichaamsbeweging, vooral wanneer ze spraken over hun lichamelijke perceptie en socio-emotionele leven. Hoge Neuroticisme correleerde met hogere negatieve affectie na de taak. Extraversie werd geassocieerd met meer regelmatige en deterministische bewegingspatronen tijdens het bespreken van lichaamsperceptie en sensorisch leven. Consciëntieusheid hing samen met lager determinisme ongeacht het onderwerp. Deze bevindingen ondersteunen het idee dat persoonlijkheidskenmerken invloed hebben op fysieke expressie van persoonlijkheid en interactie met de omgeving. Deelnemers rapporteerden minder negatieve affectie na de taak, wat suggereert dat zelfonthulling over het algemeen de affectieve toestand verbetert, behalve bij deelnemers met hoge Neuroticisme.

Hoofdstuk 5: Voorbij Woorden: Synchronisatie van spraak en Gespreksdynamiek gekoppeld aan Persoonlijkheid en Beoordelingen van de interactie

Dit hoofdstuk onderzoekt de rol van persoonlijkheid in synchronisatie van spraak tijdens gesprekken tussen jongvolwassenen. In het bijzonder werd onderzocht hoe persoonlijkheidsverschillen en gespreksonderwerpen, de interpersoonlijke synchronisatie in het gesprek, de leider-volger dynamiek, en de non-verbale dominantie voorspellen. De experimentele taak is dezelfde als in Hoofdstuk 3. Deelnemers voerden een gesprek van 15 minuten over de drie onderwerpen (introductie / zelfonthulling / argumentatie). In dit geval lag de focus op het bestuderen van hun synchronisatie van spraak en beurtwisseling (spreken-zwijgen) dynamiek, die werd beoordeeld door middel van niet-lineaire tijdreeksanalyses. Uit de tijdreeksen hebben we vijf variabelen geëxtraheerd om synchronisatie van de spraak te typeren. Beoordelingen van de deelnemers na afloop van de interactie werden gedetailleerd onderzocht met behulp van een vragenlijst over de perceptie van de interactie (Cuperman & Ickes, 2009). Associaties tussen de persoonlijkheidskenmerken Extraversie en Aangenaamheid, en de synchronisatie van spraak en de non-verbale dominantie werden getest met behulp van mixed-effects modellen.

Resultaten toonden aan dat synchronisatie van spraak en non-verbale dominantie varieerden per onderwerp, met hogere globale synchronisatie van spraak tijdens argumentatieve gesprekken. Dit laat de rol van gespreksonderwerpen zien bij het beïnvloeden van synchronisatie van spraak, hetgeen ook al in eerder onderzoek is laten zien (Fusaroli et al., 2014). Hoge Extraversie was gekoppeld aan verhoogde synchronisatie van spraak ongeacht het onderwerpen (Costa & McCrae, 1995; Lucas

& Diener, 2001). Koppels met vergelijkbare niveaus van Extraversie vertoonden meer symmetrische beurtwisselingen tijdens zelfonthulling, en de aanwezigheid van minstens één extraverte deelnemer leidde tot verhoogde synchronisatie. Extraverte deelnemers waardeerden snelle gesprekken, terwijl introverte deelnemers juist stiltes en pauzes waardeerden. Introversie voorspelde non-verbale dominantie. Hoge Aangenaamheid werd geassocieerd met verminderde synchronisatie van spraak in argumentatieve gesprekken, terwijl lage Aangenaamheid hogere synchronisatie vertoonde in deze contexten, net als in Hoofdstuk 3. Verhoogde synchronisatie was gekoppeld aan een lagere perceptie van natuurlijkheid onder Aangename individuen, wat wijst op een afweging tussen snelle dynamiek van het gesprek en 'conversatieflow'. Aangename individuen vertoonden non-verbale dominantie tijdens zelfonthulling en argumentatie, wat prosociale en wederzijdse interacties faciliteerde (Worgan & Moore, 2011).

Hoofdstuk 6: Relatie tussen temperamentdimensies en de complexiteit en stabiliteit van het motorsysteem bij zuigelingen

Dit laatste empirische hoofdstuk onderzoekt de relatie tussen de complexiteit van het motorsysteem, stabiliteit en temperamentkenmerken op 6 en 12 maanden leeftijd. De redenering is dat temperamentdimensies bij zuigelingen gedragsreacties op stimulatie beschrijven, terwijl het motorsysteem tijdens de kindertijd aanzienlijke veranderingen doormaakt. Bovendien worden beide beïnvloed door de mentale gezondheid van verzorgers. In deze studie onderzoeken we hoe temperamentkenmerken geassocieerd zijn met hoog-niveau metingen van de organisatie van het motorsysteem op 6 en 12 maanden tijdens drie verschillende soorten spel. Om de effecten van de mentale gezondheid van de verzorger vast te leggen, nemen we ook de 'anxiety' van de moeder op in onze analyses. De longitudinale steekproef bestaat uit 83 zuigelingen op 6 maanden en 59 zuigelingen op 12 maanden. Bewegingen van de ledematen werden gemeten met draagbare versnellingsmeters tijdens drie taken met hun verzorger: voorlezen, manipulerend speelgoed en schudden met de rammelaar. Met behulp van een multidimensionale niet-lineaire tijdreeksanalyse hebben we de variabelen Complexiteit en Stabiliteit berekend. Met behulp van mixed-effects modellen hebben we de voorspellende effecten van taak- en temperamentdimensies geëvalueerd, t.w. Negatieve Emotionaliteit (NEG), Positieve Affectiviteit of Surgency (PAS), en Oriëntatie- en Regulatiecapaciteit (ORC). De gegevens voor deze studie werden verzameld in het BabyLab van de Poolse Academie van Wetenschappen door medewerker en mede-auteur Zuzanna Laudańska.

Onze resultaten toonden aan dat Negatieve Affectiviteit een verhoogde Entropie en Stabiliteit van het motorsysteem voorspelde op 6 maanden en longitudinaal op 12 maanden. Temperamentdimensies gemeten op 12 maanden voorspelden echter niet de Complexiteit en Stabiliteit van het motorsysteem op dezelfde leeftijd. Op 12 maanden werden Entropie en Stabiliteit echter beïnvloed door de taak. Bovendien voorspelde hogere 'maternal anxiety' (gemeten toen de baby's 4 maanden oud waren) een verminderde Entropie en Stabiliteit van het motorsysteem op 12 maanden. Deze bevindingen hebben implicaties voor het begrijpen van de vroege ontwikkelingspaden van de dynamische organisatie van het motorsysteem, de relatie met temperament, en de invloed van de mentale gezondheid van de verzorger op de motorische ontwikkeling van baby's.

Hoofdstuk 7: Algemene Discussie

Dit hoofdstuk presenteert een algemene discussie die de bevindingen van alle studies samenvat en integreert, hun implicaties behandelt en suggesties doet voor toekomstige onderzoeksrichtingen. Ik bespreek hoe deze dissertatie significante verbanden heeft kunnen leggen tussen persoonlijkheidskenmerken en dynamische patronen en synchronisatie in zowel lichaamsbeweging als spraak. Bovendien is deze benadering effectief uitgebreid naar zuigelingen, waarbij verbanden zijn aangetoond tussen temperamentdimensies en de dynamische organisatie van ledematen—specifiek de complexiteit en stabiliteit van het motorsysteem. Er wordt besproken hoe de belichaamde en dynamische patronen niet alleen kunnen weerspiegelen, maar ook kunnen vormen wat we als persoonlijkheid beschouwen, wat de basis legt voor toekomstig empirisch onderzoek. Daarnaast worden enkele toekomstige richtingen en relevante methodologische inzichten besproken, in het bijzonder met betrekking tot het optimaal gebruik van tijdreeksanalyse, elementen om in gedachten te houden bij het interpreteren van dynamische metingen, en hoe het gebruik ervan in toekomstige studies kan worden verbeterd.

Conclusie

Deze dissertatie heeft ons begrip van de dynamische wisselwerking tussen de dynamica van gedrag (i.h.b. lichaamsbewegingen en spraak), de context (i.h.b. type gesprek en spel) en psychologische eigenschappen (i.h.b. persoonlijkheid en temperament) verdiept. Door 'enactive', belichaamde en complexe systeem perspectieven te integreren, hebben we laten zien hoe persoonlijkheid en temperament verbonden zijn met de synchronisatie tussen interacterende individuen en de dynamische organisatie van het motorsysteem. De belangrijkste bijdragen van de dissertatie zijn hieronder kort opgesomd:

Integratie van theoretische kaders: Deze dissertatie biedt een kader om de dynamische wisselwerking tussen individuen en hun omgeving te begrijpen, en presenteert persoonlijkheid als een emergente eigenschap uit interacties tussen belichaamde individuen en hun omgeving. Deze aanpak biedt mogelijkheden tot uitbreiding naar andere psychologische constructen. ***Implicaties voor persoonlijkheidstheorie:*** De bevindingen bevorderen een vloeiende, belichaamde, gesitueerde, wederkerige, zacht samengestelde en interactionistische benadering om individuele verschillen te bestuderen, met focus op dynamische interactiepatronen en stilistische verschillen in waarneming en omgang met de wereld. ***Nieuwe***

methodologische benaderingen: Gebruikmakend van niet-lineaire tijdreeksanalyses biedt deze dissertatie een gedetailleerde analyse van lichaamsbeweging en synchronisatie van spraak, waardoor patronen onthuld werden die gerelateerd zijn aan persoonlijkheidskenmerken. ***Uitbreiding naar ontwikkeling van zuigelingen:*** Het onderzoek verkent de ontwikkeling van de dynamische organisatie van het motorsysteem en de verbinding met temperament, en benadrukt de band tussen vroege ontwikkeling van lichaamscoördinatie, psychologische eigenschappen, en de geestelijke gezondheid van de moeder. ***Methodologische inzichten en beperkingen:*** Tijdreeksanalyses kent beperkingen zoals parameterinstelling en datakwaliteit, wat verdere ontwikkeling van experimentele studies aanmoedigt**.** ***Praktische toepassingen en implicaties voor onderzoek:*** Inzichten uit dit onderzoek kunnen interventies informeren en kunnen in de toekomst leiden tot diagnostische hulpmiddelen, door gebruik te maken van niet-invasieve methoden en technologie zoals draagbare sensoren en machine learning, om daarmee dynamische patronen nauwkeuriger te analyseren in alledaagse omgevingen.

Deze dissertatie legt een solide basis voor toekomstig onderzoek en biedt zowel theoretische als praktische inzichten. Het pleit voor integratie van niet-lineaire dynamica en innovatieve methodologieën om ons begrip van menselijk gedrag en ontwikkeling te verbeteren. Door enactive, belichaamde en dynamische perspectieven te omarmen, kan toekomstig onderzoek de complexiteiten van menselijk gedrag verder verkennen, leidend tot effectievere interventies en een meer omvattend en dieper begrip van persoonlijkheid, temperament en mogelijk andere psychologische constructen.

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Supplement

Supplementary Materials
Chapter 3 - Supplement contents

Figure S1: Graphical representation employed to assess interpersonal closeness (Inclusion of Other in the Self "IOS", Aron et al., 1992).

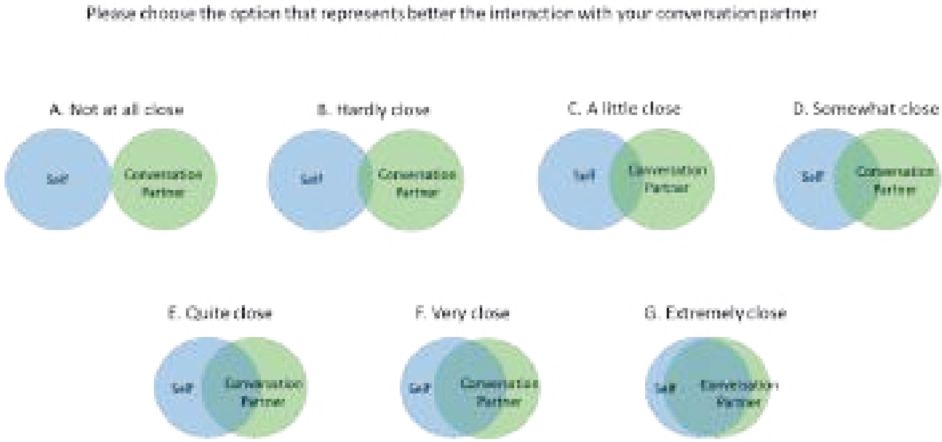
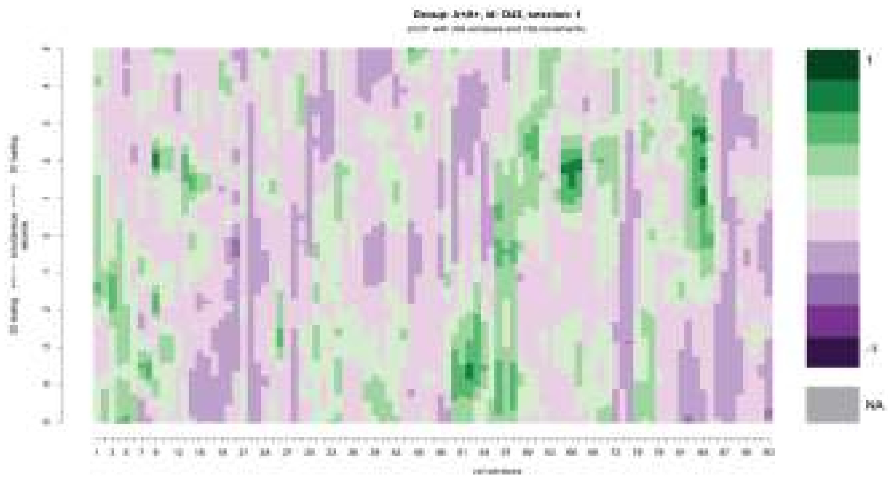


Figure S2. Heatmap of Windowed Lagged Cross Correlations over the interaction for an Agreeable dyad (A++)



Note. The heatmap is a graphical representation of the lagged cross-correlations over windows (axis X), representing the dynamics of movement for this particular dyad "A++". The green segments represent positive correlations (both subjects accelerate their movement) and purples represent negative correlations (one subject accelerates and the other decreases movement). The vertical axis represents leading behavior and time in seconds, and zero represents simultaneous movement. In this case, it is possible to appreciate a turn-taking behavior, given by the movement of one subject leading the interaction followed by the other. Hence, subject 2 leads across window 52, and subsequently subject 1 takes over the leading.

Supplement to Method S1 – Chapter 3

Items of the Self-Disclosure Task Employed in the Study
Adapted from the Closeness-Generating Procedure (Aron et al., 1997).

Set I:

1. What would constitute a "perfect" day for you?
2. For what in your life do you feel most grateful?
3. If you could wake up tomorrow having gained any quality or ability, what would it be?

Set II:

4. Is there something that you've dreamed of doing for a long time? Why haven't you done it?
5. What roles do love and affection play in your life?
6. How do you feel about your relationship with your family?

Set III:

7. If you were going to become a close friend to someone, please share what would be important for that person to know?
8. Share an embarrassing moment in your life.
9. Share a personal problem you would like to receive advice on.

Supplement to Method S2 – Chapter 3

Examples of the equations are provided below:

1. Equation of Interpersonal Synchronization (Strength) model (employing the R package "lme4"; Bates et al., 2015), given the formula:

(Synchronization~((Extraversion.A*Extraversion.B+Agreeableness.A*Agreeableness.B)*

Type_Interaction +(1|Dyad)):

$\llbracket \text{Synchronization} \rrbracket\_i \sim (N(\alpha j[i] + \beta 1(\text{Type\_Interaction2.SelfDisclosure}) + \beta 2(\text{Type\_Interaction3.Argumentative}), \sigma 2)$

$\alpha j \sim N$ (γα0 + γα1(Extraversion.A) + γα2(Extraversion.B) + γα3(Agreeableness.A) + γα4(Agreeableness.B) + γα5(Extraversion.A x Extraversion.B) + γα6(Agreeableness.A x Agreeableness.B) + γα7(Extraversion.A x Type_Interaction2.Self-disclosure) + γα8(Extraversion.A x Type_Interaction1.Argumentative) + γα9(Extraversion.B x Type_Interaction2.SelfDisclosure) + γα10(Extraversion.B x Type_Interaction1.Argumentative) + γα11(Agreeableness.A x Type_Interaction2.SelfDisclosure) + γα12(Agreeableness.A x Type_Interaction1.Argumentative) + γα13(Agreeableness.B x Type_Interaction2.SelfDisclosure) + γα14(Agreeableness.B xType_Interaction1.Argumentative)

+ γα15(Extraversion.A x Extraversion.B x Type_Interaction2.SelfDisclosure)

+ γα16(Extraversion.A x Extraversion.B x Type_Interaction 1.Argumentative)

+ γα17(Agreeableness.A x Agreeableness.B x Type_Interaction2.SelfDisclosure)

+ γα18(Agreeableness.A x Agreeableness.B x Type_Interaction1.Argumentative) σ2αj),for Dyad j = 1,…,J)

Note: The response variable Synchronization is the grand average extracted from the WLCC (strength). Fixed effects were calculated for the Extraversion and Agreeableness scores of each participant, and random effects were calculated for the "dyad" variable. The dyadic structure was preserved by computing the interaction between the scores on Extraversion and Agreeableness of each interacting partner. We added the type of conversation (introduction, self-disclosure, and argumentative), having "introduction" as the baseline category. The equations for the CRQA models follow the exact same structure, only the response variable is replaced by Determinism, Entropy, Laminarity and Mean Line, respectively.

2. Equation for post-interaction outcomes (in this case Negative Affect) (employing the R package “lme4”; Bates et al., 2015), given the formula:

Negative Affect ~ ((Extraversion.A1*Extraversion.B2+Agreeableness.A1*Agreeableness.B2) * (Sync+Determinism+Laminarity)+(1|Dyad)):

Negative Affecti ~ N(μ,α2)

$\mu = \alpha j[i] + \beta 1(\text{Extraversion.A}) + \beta 2(\text{Extraversion.B}) + \beta 3(\text{Agreeableness.A}) + \beta 4(\text{Agreeableness.B}) +$

$\beta 5(\text{Extraversion.A x Extraversion.B}) + \beta 6(\text{Agreeableness.A x Agreeableness.B})$

$\alpha j \sim N\ (\gamma\alpha 0 + \gamma\alpha 1(\text{Synchronization}) + \gamma\alpha 2(\text{Determinism}) + \gamma\alpha 3(\text{Laminarity})$

$+ \gamma\alpha 4(\text{Extraversion.A x Synchronization}) + \gamma\alpha 4(\text{Extraversion.A x Determinism})$

$+ \gamma\alpha 4(\text{Extraversion.A x Laminarity}) + \gamma\alpha 5(\text{Extraversion.B x Synchronization})$

$+ \gamma\alpha 6(\text{Extraversion.B x Determinism}) + \gamma\alpha 7(\text{Extraversion.B x Laminarity})$

$+ \gamma\alpha 8(\text{Agreeableness.A x Synchronization}) + \gamma\alpha 9(\text{Agreeableness.A x Determinism})$

$+ \gamma\alpha 10(\text{Agreeableness.A x Laminarity}) + \gamma\alpha 11(\text{Agreeableness.B x Synchronization})$

$+ \gamma\alpha 12(\text{Agreeableness.B x Determinism}) + \gamma\alpha 13(\text{Agreeableness.B x Laminarity})$

$+ \gamma\alpha 14(\text{Extraversion.A x Extraversion.B x Synchronization})$

$+ \gamma\alpha 15(\text{Extraversion.A x Extraversion.B x Determinism})$

$+ \gamma\alpha 16(\text{Extraversion.A x Extraversion.B x Laminarity})$

$+ \gamma\alpha 17(\text{Agreeableness.A x Agreeableness.B x Synchronization})$

$+ \gamma\alpha 18(\text{Agreeableness.A x Agreeableness.B x Determinism})$

$+ \gamma\alpha 19(\text{Agreeableness.A x Agreeableness.B x Laminarity}),\sigma 2\alpha j),\text{for Dyad } j = 1,\ldots,J$

Note: The response variable, in this case, is Negative Affect, but the same structure was followed for the other post-interaction outcomes (Positive Affect, Interpersonal Closeness, and Enjoyment). The predictors are the strength of synchronization (WLCC), Determinism, and Laminarity (CRQA). Fixed effects were calculated for the Extraversion and Agreeableness scores of each participant (A and B), and random effects were calculated for the “dyad” variable. The dyadic structure was preserved by computing the interaction between the scores on Extraversion and Agreeableness of each interacting partner.

Supplementary Tables

Table S1. Correlations between variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Synchronization Strength															
2. Determinism	**-.51***														
3. Entropy	**-.52***	**.99****													
4. Laminarity	-.26	**.77****	**.82****												
5. Mean Line	-.48	**.97****	**.99****	**.84****											
6. Agreeableness	-.37	.44	.48	.39	.45										
7. Extraversion	-.12	.11	.15	.08	.14	.49									
8. Neuroticism	.02	-.28	-.33	-.32	-.34	**-.60***	**-.88****								
9. Conscientiousness	-.46	.23	.23	.09	.19	.47	**.50***	**-.52***							
10. Openness	-.44	.25	.28	.19	.28	**.55***	.45	-.31	.30						
11. Positive Affect Pre	-.15	-.11	-.07	.03	-.07	.15	**.65****	**-.56***	**.53***	.18					
12. Positive Affect Post	-.13	-.11	-.07	.11	-.06	.18	**.61***	**-.55***	.48	.14	**.96****				
13. Negative Affect Pre	.06	**-.53***	**-.57***	**-.69****	**-.56***	**-.65****	**-.62****	**.73****	-.39	-.36	-.43	-.49			
14. Negative Affect Post	-.05	-.37	-.42	**-.61***	**-.41**	**-.67****	**-.58***	**.68****	-.34	-.32	-.43	-.49	**.95****		
15. Interpersonal Closeness	.01	-.24	-.23	-.02	-.25	.07	.28	-.15	.26	.12	**.51***	**.61***	-.36	-.41	
16. Enjoyment	.11	-.11	-.08	.15	-.08	.28	.38	-.36	.22	.20	**.55***	**.64****	**-.58***	**-.65****	**.81****

Note. * indicates $p < .05$. ** indicates $p < .01$.

Table S2. Mixed-Effects Models predicting Synchronization Strength, and Dynamic Organization: Determinism, Entropy, Mean Line, and Laminarity. N = 112

	M1. Synchronization strength			M2. Determinism			M3. Entropy			M4. Laminarity			M5. Mean Line		
Predictors	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**
Intercept	-0.026 (-0.15)	-0.04–-0.02	**<0.000 *****	0.929 (-0.09)	0.92–0.94	<0.000 ***	2.278 (-0.17)	2.21–2.34	**<0.000*****	0.967 (-0.13)	0.97–0.97	<0.000***	5.717 (-0.15)	5.33–6.10	**<0.000 *****
Extraversion A	-0.003 (-0.09)	-0.01–0.01	0.784	-0.000 (-0.01)	-0.01–0.01	0.985	-0.005 (-0.02)	-0.07–0.06	0.920	-0.004 (-0.23)	-0.01–0.00	0.466	0.026 (0.02)	-0.37-0.43	0.929
Extraversion B	0.002 (0.06)	-0.01 – 0.01	0.935	-0.003 (-0.07)	-0.01–0.01	0.985	-0.039 (-0.15)	-0.11-0.03	0.567	-0.002 (-0.15)	-0.01–0.00	0.552	-0.274 (-0.18)	-0.70–0.15	0.538
Agreeableness A	-0.005 (-0.13)	-0.02 – 0.01	0.684	0.002 (0.05)	-0.01–0.01	0.985	0.031 (0.11)	-0.04–0.11	0.677	0.002 (0.13)	-0.00–0.01	0.552	0.197 (0.13)	-0.24–0.63	0.709
Agreeableness B	-0.006 (-0.15)	-0.02 – 0.00	0.612	0.010 (0.27)	0.00 – 0.02	0.429	0.108 (0.40)	0.04 – 0.18	**0.030***	0.002 (0.13)	-0.00–0.01	0.552	0.469 (0.31)	0.06–0.88	0.129
Interaction [Self-disclosure]	0.014 (0.39)	0.00 – 0.02	**0.042***	-0.001 (-0.04)	-0.01–0.01	0.985	0.038 (0.14)	-0.03–0.11	0.567	0.002 (0.15)	-0.00–0.01	0.466	0.166 (0.11)	-0.23–0.56	0.709
Interaction [Argumentative]	0.002 (0.05)	-0.01 – 0.01	0.935	0.010 (0.28)	-0.00–0.02	0.429	0.092 (0.34)	0.02 – 0.16	0.070.	0.004 (0.25)	0.00–0.01	0.466	0.457 (0.30)	0.06–0.85	0.129
Extrav. A * Extrav. B *	0.012 (0.34)	0.00 – 0.02	0.139	-0.002 (-0.05)	-0.01–0.01	0.985	-0.020 (-0.08)	-0.10–0.06	0.751	0.002 (0.15)	-0.00–0.01	0.552	-0.044 (-0.03)	-0.50–0.41	0.929
Agreeab. A *Agreeab. B	-0.004 (-0.12)	-0.01 – 0.00	0.612	0.000 (0.01)	-0.01–0.01	0.985	0.007 (0.03)	-0.05–0.06	0.876	-0.002 (-0.15)	-0.01–0.00	0.466	0.040 (0.03)	-0.27–0.35	0.929
Extrav. A * T.I. [Self-disclosure]	-0.000 (-0.01)	-0.01 – 0.01	0.935	0.008 (0.23)	-0.00–0.02	0.557	0.062 (0.23)	-0.01–0.13	0.399	0.004 (0.24)	-0.00–0.01	0.466	0.162 (0.11)	-0.25–0.57	0.709
Extrav. A* T.I. [Argumentative]	0.003 (0.09)	-0.01 – 0.01	0.784	-0.001 (-0.02)	-0.01–0.01	0.985	0.019 (0.07)	-0.05–0.09	0.750	0.001 (0.09)	-0.00–0.01	0.644	-0.019 (-0.01)	-0.43–0.39	0.929

Table S2. Mixed-Effects Models predicting Synchronization Strength, and Dynamic Organization: Determinism, Entropy, Mean Line, and Laminarity. N = 112 (continued)

	M1. Synchronization strength			M2. Determinism			M3. Entropy			M4. Laminarity			M5. Mean Line		
Predictors	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**
Extrav. B * T.I. Self-disclosure	0.006 (0.16)	-0.01 – 0.02	0.624	0.003 (0.08)	-0.01– 0.02	0.985	0.054 (0.20)	-0.02– 0.13	0.457	0.001 (0.09)	-0.00– 0.01	0.644	0.360 (0.24)	-0.08– 0.80	0.452
Extrav. B * T.I. Argumentative	-0.007 (-0.19)	-0.02 – 0.00	0.612	0.006 (0.16)	-0.01– 0.02	0.805	0.073 (0.20)	-0.00– 0.15	0.343	0.003 (0.21)	-0.00– 0.01	0.466	0.712 (0.47)	0.27 – 1.15	**0.02***
Agreeab. A* T.I. [Self-dis-closure]	-0.001 (-0.03)	-0.01 – 0.01	0.935	-0.011 (-0.30)	-0.02– 0.00	0.429	-0.062 (0.27)	-0.14– 0.02	0.439	-0.003 (-0.18)	-0.01– 0.00	0.466	-0.141 (-0.09)	-0.59– 0.30	0.800
Agreeab. A * T.I. [Argumen-tative]	0.010 (0.27)	-0.00 – 0.02	0.367	0.000 (0.00)	-0.01– 0.01	0.985	-0.015 (-0.23)	-0.09- 0.06	0.818	-0.001 (-0.04)	-0.01– 0.00	0.825	-0.097 (-0.06)	-0.54– 0.35	0.929
Agreeab.B * T.I. [Self-dis-closure]	0.001 (0.02)	-0.01 – 0.01	0.935	0.008 (0.21)	-0.00– 0.02	0.585	-0.028 (-0.06)	-0.10- 0.05	0.677	0.001 (0.04)	-0.00– 0.00	0.825	-0.283 (-0.19)	-0.70– 0.14	0.537
Agreeab. B * T.I. [Argumen-tative]	-0.001 (-0.02)	-0.01 – 0.01	0.935	-0.007 (-0.18)	-0.02 0.01	0.690	-0.051 (-0.11)	-0.13– 0.02	0.457	0.000 (-0.01)	-0.00– 0.00	0.936	-0.227 (-0.15)	-0.65– 0.19	0.668
Extrav. A * Extrav. B * T.I.[Self-disclo-sure]	-0.018 (-0.50)	-0.03 – -0.01	**0.037***	0.000 (0.01)	-0.01– 0.01	0.985	0.044 (-0.19)	-0.04– 0.13	0.567	-0.001 (-0.06)	-0.01– 0.00	0.788	0.338 (0.22)	-0.13– 0.80	0.533
(Extrav. A * Extrav. B)* T.I.[Argumen-tative]	-0.004 (-0.11)	-0.02 – 0.01	0.783	-0.003 (-0.08)	-0.02– 0.01	0.985	-0.028 (0.16)	-0.11– 0.05	0.693	-0.002 (-0.11)	-0.01– 0.00	0.630	-0.219 (-0.14)	-0.68– 0.25	0.709
(Agreeab. A *Agreeab. B) * T.I.[Self-disclo-sure]	0.007 (0.19)	-0.00 – 0.02	0.367	0.007 (0.19)	-0.00– 0.02	0.533	0.024 (-0.11)	-0.03– 0.08	0.677	0.002 (0.15)	-0.00– 0.01	0.466	0.031 (0.02)	-0.29– 0.35	0.929

Table S2. Mixed-Effects Models predicting Synchronization Strength, and Dynamic Organization: Determinism, Entropy, Mean Line, and Laminarity. N = 112 (continued)

	M1. Synchronization strength			M2. Determinism			M3. Entropy			M4. Laminarity			M5. Mean Line		
Predictors	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**
(Agreeab.A* Agreeab.B) * T.I.[Argumen-tative]	0.001 (0.03)	-0.01 – 0.01	0.935	-0.001 (-0.03)	-0.01– 0.01	0.985	-0.001 (0.09)	-0.06- 0.06	0.966	0.002 (0.13)	-0.00– 0.01	0.466	0.057 (0.04)	-0.26– 0.38	0.929
Random Effects															
Σ / σ² Dyad	0.027 / 0.0007			0.029 / 0.0003			0.180 / 0.0325			0.010 / 0.0001			1.021 / 1.0421		
τ00 Dyad	0.0004			0.0009			0.0262			0.0001			0.9264		
ICC	0.381			0.272			0.446			0.542			0.471		
Observations	168			168			168			168			168		
Marginal R2/ Conditional R	0.149 / 0.474			0.160 / 0.388			0.178 / 0.545			0.085 / 0.581			0.136 / 0.542		

Note: * indicates $p < .05$. ** indicates $p < .01$. ***indicates $p <.000$. "A" and "B" refer to participant A and participant B. p-values were corrected following the Benjamini-Hochberg (Benjamini & Hochberg, 1995) False Discovery Rate procedure. Estimate corresponds to the unstandardized estimate coefficient. β = Standardized beta weights. Extrav. A = Extraversion participant A. Extrav. B = Extraversion participant B. Agreeab. A = Agreeableness participant A. Agreeab. B = Agreeableness participant B. TI: Type Interaction.

Table S3 Linear Models predicting the post-interaction outcomes

	Positive Affect			Negative Affect			Interpersonal Closeness			Enjoyment		
Predictors	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**
Intercept	15.83 (0.03)	15.05 – 16.61	**<0.000*** **	6.35 (-0.02)	5.95 – 6.76	**<0.000*** **	4.75 (0.05)	4.53 – 4.98	**<0.000*** **	3.85 (0.02)	3.72 – 3.98	**<0.000*** **
Extraver-sion A	1.29 (0.32)	0.52 – 2.07	**0.017***	-0.24 (-0.10)	-0.65 – 0.16	0.543	0.17 (0.15)	-0.05 – 0.39	0.326	0.07 (0.09)	-0.06 – 0.19	0.452
Extraver-sion B	-0.17 (-0.04)	-0.94 – 0.61	0.785	0.22 (0.09)	-0.18 – 0.63	0.543	-0.19 (-0.17)	-0.41 – 0.03	0.326	0.07 (-0.13)	-0.06 – 0.19	0.305
Agreeable-ness A	0.32 (0.08)	-0.56 – 1.20	0.618	-0.83 (-0.34)	-1.29 – -0.37	**0.006** **	-0.04 (-0.03)	-0.29 – 0.21	0.809	0.18 (0.26)	0.04 – 0.33	**0.061.**
Agreeable-ness B	0.01 (0.00)	-0.86 – 0.89	0.974	-0.45 (-0.18)	-0.90 – 0.01	0.219	0.05 (0.04)	-0.20 – 0.30	0.809	0.10 (0.14)	-0.05 – 0.24	0.337
Synchroni-zation	-0.60 (-0.15)	-1.31 – 0.11	0.415	-0.31 (-0.13)	-0.68 – 0.05	0.286	-0.07 (-0.06)	-0.28 – 0.13	0.647	0.10 (0.14)	-0.02 – 0.22	0.218
Determin-ism	-1.87 (-0.47)	-3.78 – 0.04	0.302	0.45 (0.19)	-0.54 – 1.44	0.568	-0.73 (-0.64)	-1.29 – -0.17	0.154	-0.06 (-0.09)	-0.38 – 0.25	0.780
Laminarity	2.14 (0.54)	0.33 – 3.95	0.145	-1.01 (-0.42)	-1.95 – -0.07	0.165	0.58 (0.51)	0.05 – 1.11	0.154	0.16 (0.23)	-0.14 – 0.46	0.452
E_A * E_B	-0.08 (-0.02)	-1.12 – 0.96	0.917	-0.24 (-0.10)	-0.78 – 0.30	0.568	-0.35 (-0.31)	-0.65 – -0.04	0.154	-0.21 (-0.31)	-0.39 – -0.04	**0.061.**
A_A * A_B	-0.14 (-0.03)	-0.93 – 0.66	0.793	0.65 (0.27)	0.23 – 1.06	**0.022***	0.07 (0.06)	-0.17 – 0.30	0.729	-0.07 (-0.10)	-0.20 – 0.07	0.452

Table S3. Linear Models predicting the post-interaction outcomes (continued)

	Positive Affect			Negative Affect			Interpersonal Closeness			Enjoyment		
Predictors	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**
E_A * Synchronization	1.18 (0.30)	0.30 – 2.06	0.083	0.51 (0.21)	0.05 – 0.97	0.165	0.12 (0.10)	-0.14 – 0.37	0.598	0.18 (0.26)	0.04 – 0.33	**0.061.**
E_A * Determinism	0.74 (0.18)	-0.91 – 2.39	0.611	0.06 (0.03)	-0.79 – 0.92	0.997	-0.06 (-0.05)	-0.52 – 0.41	0.809	0.25 (0.36)	-0.02 – 0.52	0.184
E_A * Laminarity	-0.90 (-0.23)	-2.42 – 0.61	0.611	-0.24 (-0.10)	-1.02 – 0.55	0.712	-0.18 (-0.16)	-0.62 – 0.26	0.647	-0.44 (-0.63)	-0.69 – -0.19	**0.010***
E_B * Synchronization	0.50 (0.13)	-0.38 – 1.38	0.611	-0.00 (-0.00)	-0.46 – 0.46	0.999	0.06 (0.05)	-0.20 – 0.31	0.795	0.08 (0.11)	-0.07 – 0.22	0.452
E_B * DET	1.13 (0.28)	-0.52 – 2.78	0.580	-0.12 (-0.05)	-0.97 – 0.74	0.960	0.23 (0.20)	-0.24 – 0.70	0.598	0.21 (0.30)	-0.06 – 0.48	0.279
E_B * LAM	-0.74 (-0.19)	-2.26 – 0.77	0.611	-0.37 (-0.15)	-1.15 – 0.42	0.568	0.06 (0.05)	-0.38 – 0.50	0.809	-0.28 (-0.40)	-0.53 – -0.02	0.101
A_A * Synchronization	-0.49 (-0.12)	-1.54 – 0.57	0.611	0.01 (0.01)	-0.53 – 0.56	0.991	-0.24 (-0.21)	-0.54 – 0.06	0.326	-0.23 (-0.33)	-0.40 – -0.05	**0.061.**
A_A * DET	-0.69 (-0.17)	-2.37 – 0.99	0.611	0.72 (0.30)	-0.15 – 1.59	0.289	-0.37 (-0.32)	-0.86 – 0.12	0.326	-0.11 (-0.16)	-0.39 – 0.17	0.542
A_A * LAM	-0.69 (0.33)	-2.37 – 0.99	0.415	-0.25 (-0.10)	-1.09 – 0.59	0.712	0.29 (0.26)	-0.18 – 0.76	0.445	-0.03 (-0.05)	-0.30 – 0.23	0.866

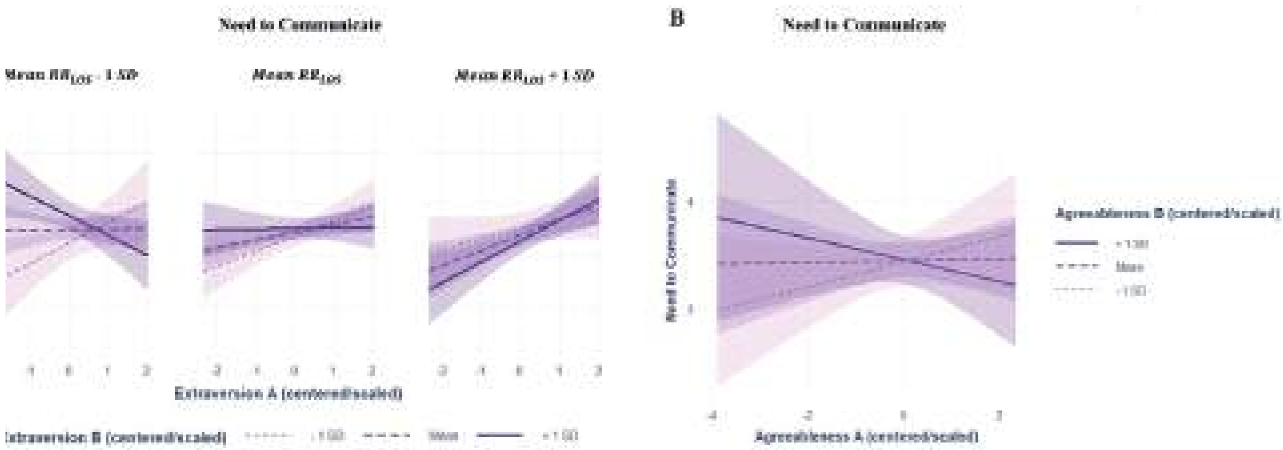
Table S3. Linear Models predicting the post-interaction outcomes (continued)

	Positive Affect			Negative Affect			Interpersonal Closeness			Enjoyment		
Predictors	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**	**Estimate (β)**	**CI**	**p**
A_B * Synchronization	0.37 (0.09)	-0.68 – 1.42	0.618	-0.25 (0.11)	-1.09 – 0.59	0.568	-0.11 (--0.09)	-0.41 – 0.19	0.647	-0.16 (-0.23)	-0.33 – 0.02	0.184
A_B * DET	-0.69 (-0.17)	-2.37 – 0.99	0.611	0.76 (0.31)	-0.12 – 1.63	0.286	-0.29 (-0.25)	-0.78 – 0.20	0.466	-0.09 (-0.13)	-0.37 – 0.19	0.625
A_B * LAM	0.69 (0.17)	-0.93 – 2.31	0.611	-0.49 (-0.20)	-1.33 – 0.36	0.543	0.53 (0.46)	0.06 – 1.00	0.153	-0.02 (-0.03)	-0.29 – 0.24	0.892
(E_A *E_B) * Synchronization	-0.33 (-0.08)	-1.67 – 1.01	0.761	-0.82 (-0.34)	-1.52 – -0.12	0.149	0.14 (0.12)	-0.25 – 0.53	0.647	-0.06 (-0.08)	-0.28 – 0.17	0.714
(E_A * E_B) * DET	0.37 (0.09)	-1.75 – 2.48	0.793	0.52 (0.21)	-0.58 – 1.62	0.568	0.48 (0.42)	-0.14 – 1.10	0.326	0.38 (0.55)	0.03 – 0.73	0.101
(E_A * E_B) * LAM	-0.47 (-0.12)	-1.81 – 0.86	0.618	-0.55 (-0.23)	-1.25 – 0.14	0.289	-0.32 (-0.28)	-0.71 – 0.07	0.326	-0.33 (-0.48)	-0.55 – -0.11	**0.031***
(A_A* A_B) * Synchronization	0.52 (0.13)	-0.62 – 1.66	0.611	-0.23 (-0.10)	-0.82 – 0.36	0.606	0.06 (0.05)	-0.27 – 0.39	0.809	-0.01 (-0.01)	-0.20 – 0.18	0.936
(A_A* A_B) * DET	-0.75 (-0.19)	-2.25 – 0.75	0.611	-0.05 (-0.02)	-0.83 – 0.73	0.997	-0.32 (-0.28)	-0.75 – 0.12	0.339	-0.17 (-0.25)	-0.42 – 0.08	0.329
(A_A* A_B) *LAM	1.30 (0.33)	-0.65 – 3.26	0.580	-0.02 (-0.01)	-1.03 – 0.99	0.999	0.64 (0.56)	0.07 – 1.20	0.154	-0.14 (-0.20)	-0.46 – 0.18	0.523
$σ^2$ / τ00 Dyad		10.85 / 0.00		2.93 / 0.00			0.82 / 0.05			0.30 / 0.00		
N Dyad/ Observations		56 / 112		56 / 112			56 / 112			56 / 112		
Marginal R2		0.314		0.493			0.321			0.376		

*Note: * indicates p < .05. ** indicates p < .01. ***indicates p <.000. "A" and "B" refer to participant A and participant B. DET = Determinism. LAM = Laminarity. p-values were corrected following the Benjamini-Hochberg (Benjamini & Hochberg, 1995) False Discovery Rate procedure. Only marginal R-squared are reported on these models since the predictions are based on Synchronization, Determinism, and Laminarity of the full interactions, always preserving the dyadic structure and effects. β = Standardized beta weights. E_A = Extraversion participant A. E_B = Extraversion participant B. A_A = Agreeableness participant A. A_B = Agreeableness participant B.*

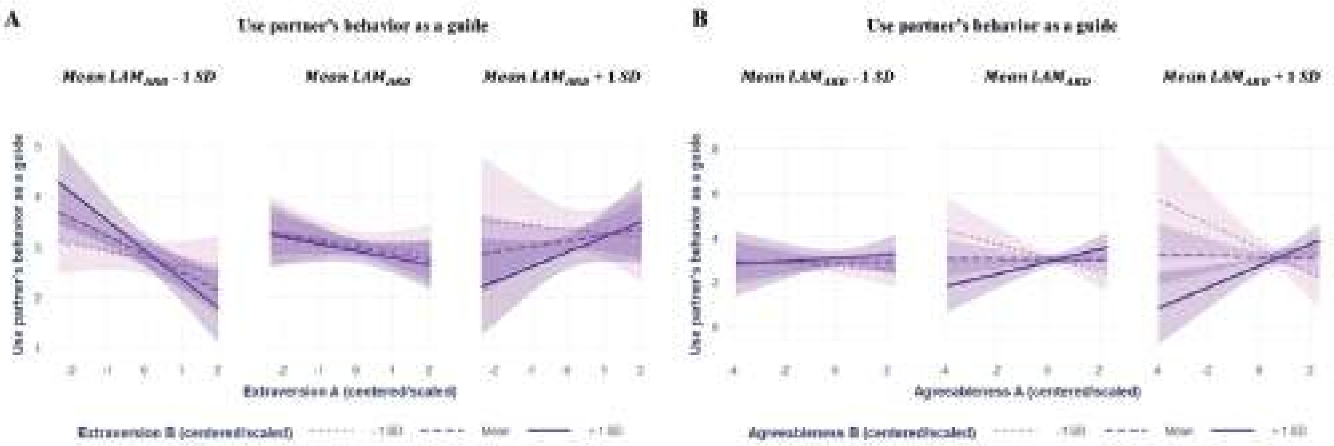
Chapter 5 - Supplement contents
Supplementary Figures

Figure S.1. Need to communicate predicted by Extraversion, RR_{LOS}, and Agreeableness



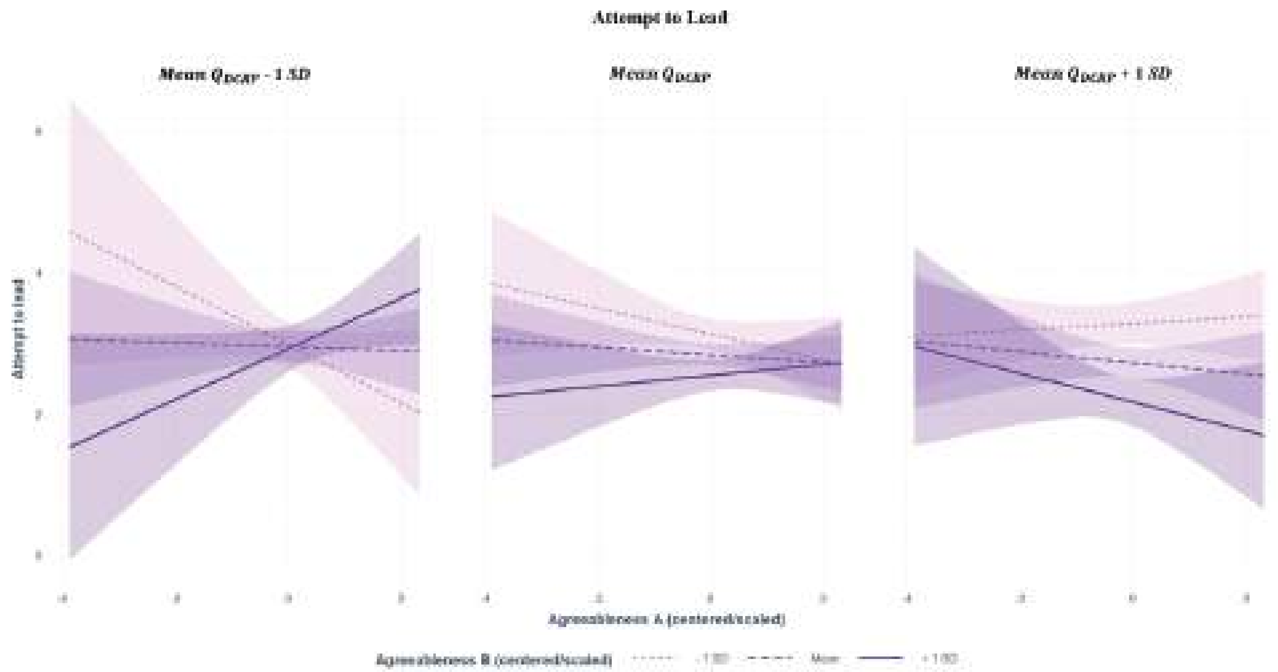
Note: Panel A shows the effects of the Extraversion scores of both conversation partners and RR_{LOS} (-1SD, mean, and +1SD) on the reported need to communicate (y-axis) (Table S1, Model 1). Panel B shows the effects of the Agreeableness scores of both conversation partners on the reported need to communicate (y-axis) (Table S4, Model 1). RR_{LOS}= Recurrence rate across the line of synchrony (lag-zero).

Figure S.2. Use of the partner's behavior as a guide predicted by Extraversion, LAM_{ARD}, and Agreeableness



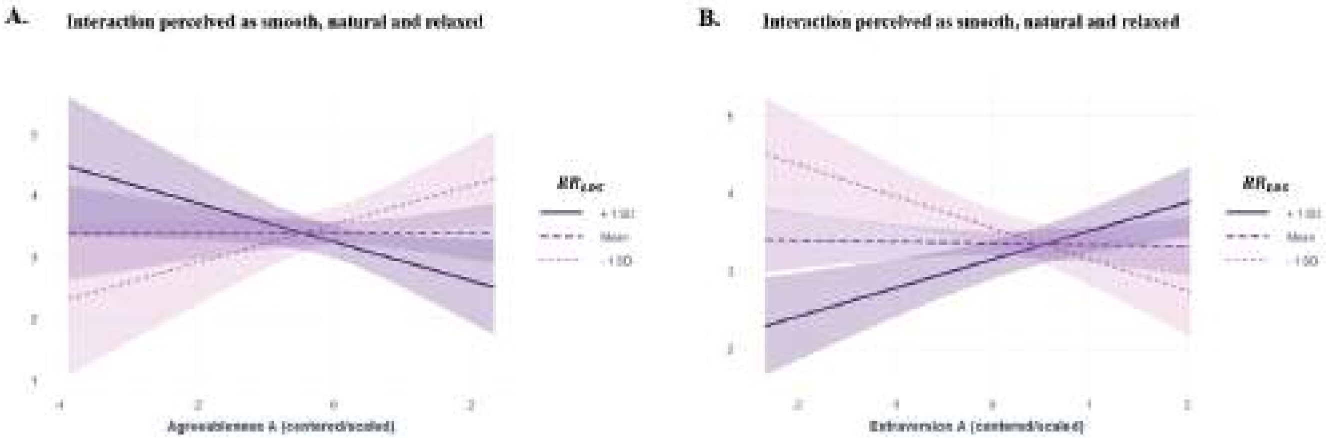
Note: Panel A shows the effects of the Extraversion scores of both conversation partners and LAM_{ARD} (-1SD, mean, and +1SD) on the reported use of the partner's behavior as a guide (y-axis) (Table S2, Model 2). Panel B shows the effects of the Agreeableness scores of both conversation partners and LAM_{ARD} (-1SD, mean, and +1SD) on the reported use of the partner's behavior as a guide (y-axis) (Table S5, Model 2). LAM_{ARD}= Laminarity absolute relative difference (asymmetries in nonverbal interactional dominance).

Figure S.3. Attempt to lead the conversation predicted by Agreeableness and Q_{DCRP}



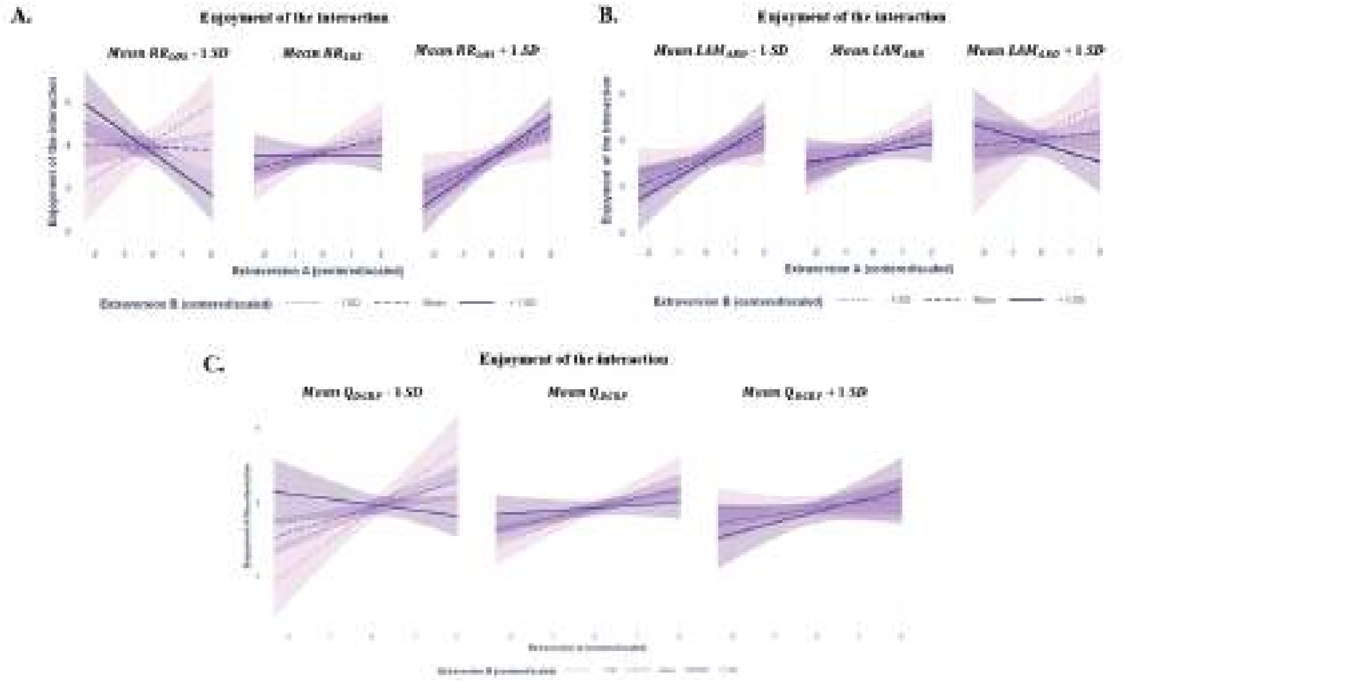
Note: The figure shows the effects of the Agreeableness scores of both conversation partners and Q_{DCRP} (-1SD, mean, and +1SD) on the reported attempt to lead the conversation (y-axis) (Table S6, Model 3). Q_{DCRP}= Quotient of Diagonal Cross Recurrence Profile (balance in leader-follower dynamics).

Figure S.4. Interaction perceived as smooth/natural/relaxed predicted by Agreeableness and RR_{LOS}, and the reported Desire to interact in the future predicted by Extraversion



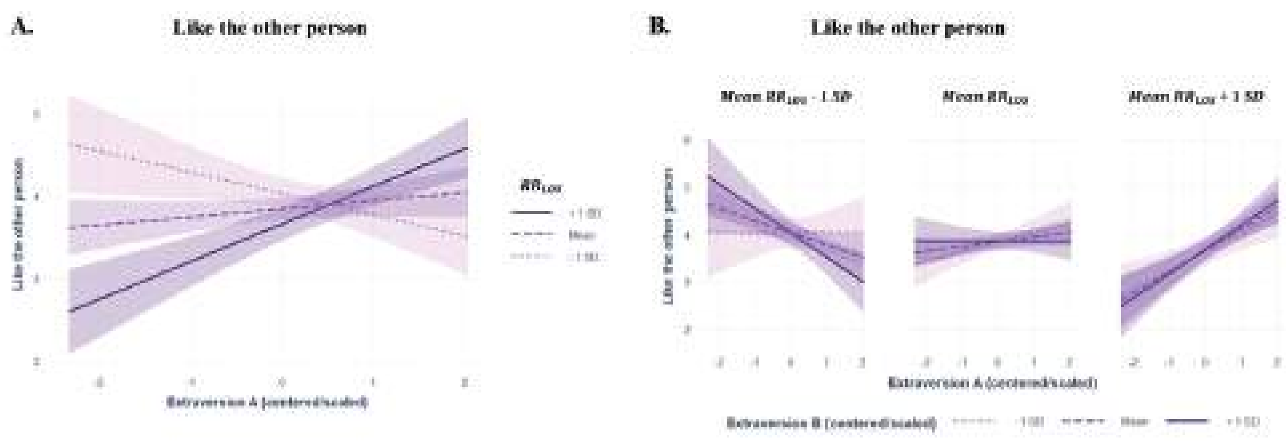
Note: Panel A shows the effects of the Agreeableness of one conversation partner and RR_{LOS} (-1SD, mean, and +1SD) on the reported interaction perceived as smooth/natural/relaxed (y-axis) (Table S4, Model 6). Panel B shows the effects of the Extraversion scores of one conversation partner and RR_{LOS} (-1SD, mean, and +1SD) on the reported desire to interact in the future (y-axis) (Table S1, Model 10). RR_{LOS}= Recurrence rate across the line of synchrony (lag-zero).

Figure S.5. Enjoyment of the interaction predicted by Extraversion, *RR_{LOS}, LAM_{ARD}, and Q_{DCRP}*



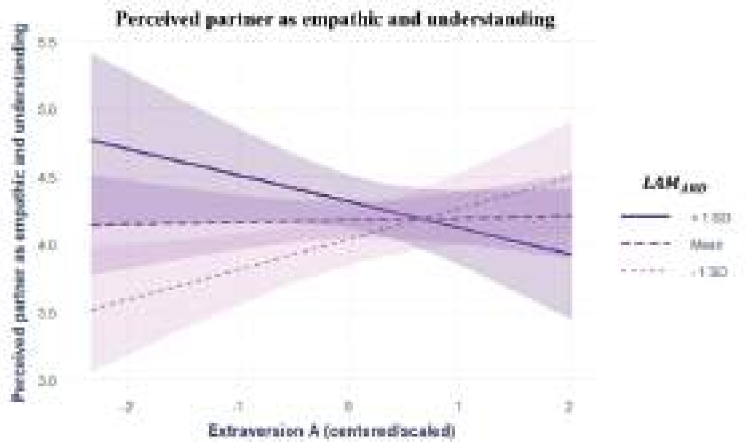
Note: Panel A shows the effects of the Extraversion scores of both conversation partners and RR_{LOS} (-1SD, mean, and +1SD) on the enjoyment of the interaction (y-axis) (Table S1, Model 11). Panel B shows the effects of the Extraversion scores of both conversation partners and LAM_{ARD} (-1SD, mean, and +1SD) on the enjoyment of the interaction (y-axis) (Table S2, Model 11). Panel C shows the effects of the Extraversion scores of both conversation partners and Q_{DCRP} (-1SD, mean, and +1SD) on the enjoyment of the interaction (y-axis) (Table S3, Model 11). RR_{LOS}= Recurrence rate across the line of synchrony (lag-zero). Q_{DCRP}= Quotient of Diagonal Cross Recurrence Profile (balance in leader-follower dynamics). LAM_{ARD}= Laminarity absolute relative difference (asymmetries in nonverbal interactional dominance).

Figure S.6. Liked the other person predicted by Extraversion and RR_{LOS}



Note: Panel A shows the effects of the Extraversion scores of one conversation partner and RR_{LOS} (-1SD, mean, and +1SD) on the reported liking of the other person (y-axis) (Table S1, Model 14). Panel B shows the effects of the Extraversion scores of both conversation partners and RR_{LOS} (-1SD, mean, and +1SD) on the reported liking of the other person (y-axis) (Table S1, Model 14). RR_{LOS}= Recurrence rate across the line of synchrony (lag-zero).

Figure S.7. Perceived partner as empathic and understanding predicted by Extraversion and *LAM_{ARD}*



Note: The figure shows the effects of the Extraversion scores of one conversation partner and LAM_{ARD} (-1SD, mean, and +1SD) on the reported perception of the partner as empathic and understanding (y-axis) (Table S2, Model 15). LAM_{ARD}= Laminarity absolute relative difference (asymmetries in nonverbal interactional dominance).

Chapter 5 - Supplement contents
Supplementary Tables

Table S.1. General Linear Models predicting Perception of the Interaction variables from RR_{LoS} and Extraversion. Ni=100 participants

	M1.	M2.	M3.	M4.	M5.	M6.	M7.	M8.	M9.	M10.	M11.	M12.	M13.	M14.	M15.
Predictor	β	β	β	β	β	β	β	β	β	β	β	β	β	β	β
Intercept	**0.03*** **	**.03*** **	**-0.01*** **	**-0.01*** **	**-0.03*** **	**0.03*** **	**0.00*** **	**-0.01*** **	**-0.01*** **	**-0.02*** **	**0.00*** **	**-0.01*** **	**-0.00*** **	**-0.01*** **	**-0.01*** **
(E_A)	-1.24	-0.07	0.17	0.04	-0.18	0.25	0.10	-0.08	0.26	**-0.02*** **	0.23	0.00	0.17	**0.14*** **	0.06
(E_B)	**2.36***	-0.05	-0.18	0.03	-0.03	0.03	-0.04	-0.05	0.08	-0.09	-0.10	-0.19	0.04	0.01	-0.02
RR_{LoS}	-0.73	-0.03	0.12	-0.12	-0.01	-0.11	**-0.31***	-0.21	-0.15	-0.24*	-0.18	-0.09	-0.07	**-0.25***	-0.18
E_A * E_B	**-3.22****	-0.15	0.14	-0.04	0.19	-0.26	-0.10	0.11	0.02	-0.14	**-0.23*** **	-0.04	-0.09	**-0.14***	-0.10
E_A *RR_{LoS}	**1.74.**	-0.28	-0.16	-0.01	-0.08	0.10	0.26	0.05	0.17	**0.46*** **	**0.28***	0.09	0.26	**0.49*** **	0.30
E_B * RR_{LoS}	**-2.29***	0.14	-0.04	0.23	0.14	0.03	-0.09	-0.10	-0.22	0.12	0.10	0.23	-0.07	0.02	-0.00
E_A * E_B * RR_{LoS}	**3.19****	0.07	-0.04	0.00	-0.21	0.19	0.18	-0.10	0.25	0.08	**0.42*** **	-0.04	0.25	**0.21***	0.17
AIC	218.07	257.66	244.50	336.89	286.50	262.91	228.14	271.69	212.42	246.28	194.28	285.85	230.59	206.48	210.09

*Note: **β** = standardized beta weights. * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p-values were corrected in the full model by Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). EA=Extraversion participant A, EB=Extraversion participant B. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled. M1= Inclination for communication; M2= Using partner's behavior as a guide for own behavior; M3= Attempts to lead the conversation; M4= Feeling self-conscious during the conversation; M5= Conversation seemed awkward, forced and strained; M6= Conversation seemed smooth, natural, and relaxed; M7= Conversation felt involving; M8= Felt put down, patronized or rejected by partner; M9= Felt accepted and respected by partner; M10= Desire to interact more with partner in the future; M11= Enjoyment of the interaction; M12= Tried to accommodate to fit in partner's behavior; M13= Felt comfortable around the partner; M14= Liked conversation partner; M15= Perceived partner as empathic and understanding.* RR_{LOS}= *Recurrence rate across the line of synchrony (lag-zero).*

Table S.2. General Linear Models predicting Perception of the Interaction variables from LAM_{ARD} and Extraversion. Ni=100 participants

	M1.	M2.	M3.	M4.	M5.	M6.	M7.	M8.	M9.	M10.	M11.	M12.	M13.	M14.	M15.
Predictor	β	β	β	β	β	β	β	β	β	β	β	β	β	β	β
Intercept	**0.01*** **	**0.03*** **	**-0.04*** **	**0.02*** **	**0.02*** **	**-0.00*** **	**-0.00*** **	**-0.01*** **	**-0.03*** **	**0.04*** **	**0.00*** **	**0.04*** **	**-0.01*** **	**0.02*** **	**0.03*** **
(E_A)	**0.20***	**-0.14****	0.18	0.02	-0.22	0.28	0.09	-0.07	**0.25****	0.00	**0.23***	-0.04	0.20	**0.16****	**0.02***
(E_B)	0.04	-0.08	-0.14	0.03	-0.04	0.04	-0.09	-0.07	0.03	-0.12	-0.13	-0.21	0.01	-0.03	-0.09
LAM_{ARD}	0.12	-0.36	-0.07	0.06	-0.16	0.23	0.25	-0.14	0.12	0.13	**0.29***	0.04	0.14	0.20	0.21
E_A * E_B	-0.04	**0.27***	0.11	-0.02	0.15	-0.22	-0.02	0.03	0.09	-0.08	-0.11	0.04	-0.01	-0.05	0.01
E_A * LAM_{ARD}	-0.20	**-0.18***	0.11	0.10	-0.04	0.08	-0.17	-0.05	-0.22	-0.18	-0.14	-0.06	-0.14	-0.27	**-0.31***
E_B * LAM_{ARD}	0.16	-0.18	0.10	-0.19	-0.20	0.11	0.09	-0.03	0.11	0.04	-0.04	-0.13	0.08	0.06	-0.05
E_A * E_B * LAM_{ARD}	-0.03	**0.23***	0.03	0.02	0.10	-0.11	-0.08	-0.07	-0.17	0.06	**-0.25***	0.21	-0.12	-0.10	-0.07
AIC	231.03	249.74	245.47	336.82	283.29	257.87	234.89	76.44	219.11	260.93	206.71	285.03	237.79	224.06	211.54

*Note: **β** = standardized beta weights. * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p-values were corrected in the full model by Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). EA=Extraversion participant A, EB=Extraversion participant B. ICC = Intraclass Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled. M1= Inclination for communication; M2= Using partner's behavior as a guide for own behavior; M3= Attempts to lead the conversation; M4= Feeling self-conscious during the conversation; M5= Conversation seemed awkward, forced and strained; M6= Conversation seemed smooth, natural, and relaxed; M7= Conversation felt involving; M8= Felt put down, patronized or rejected by partner; M9= Felt accepted and respected by partner; M10= Desire to interact more with partner in the future; M11= Enjoyment of the interaction; M12= Tried to accommodate to fit in partner's behavior; M13= Felt comfortable around the partner; M14= Liked conversation partner; M15= Perceived partner as empathic and understanding.* LAM_{ARD}*= Laminarity absolute relative difference (asymmetries in nonverbal interactional dominance).*

Table S.3. General Linear Models predicting Perception of the Interaction variables from Q_{DCRP} and Extraversion. Ni=100 participants

	M1.	M2.	M3.	M4.	M5.	M6.	M7.	M8.	M9.	M10.	M11.	M12.	M13.	M14.	M15.
Predictor	β	β	β	β	β	β	β	β	β	β	β	β	β	β	β
Intercept	**0.02*** **	**-0.01*** **	**-0.03*** **	**-0.05*** **	**-0.04*** **	**0.05*** **	**0.04*** **	**-0.02*** **	**0.01*** **	**0.02** **	**0.05*** **	**-0.00*** **	**0.01*** **	**-0.00*** **	**-0.00*** **
(E_A)	0.26	-0.19	0.13	-0.08	-0.26	0.34	0.21	-0.10	0.35	0.07	**0.36***	-0.02	0.24	0.22	0.10
(E_B)	0.06	-0.08	-0.20	-0.03	-0.06	0.10	-0.01	-0.10	0.08	-0.08	-0.01	-0.18	0.03	-0.01	-0.05
Q_{DCRP}	0.01	0.01	-0.11	-0.01	-0.14	0.17	0.00	-0.11	0.05	0.06	-0.02	-0.01	0.05	0.07	-0.05
$E_A * E_B$	-0.03	-0.14	0.11	-0.06	0.11	-0.26	-0.12	0.01	0.10	-0.20	**-0.26****	-0.02	-0.02	-0.19	-0.16
$E_A * Q_{DCRP}$	0.02	-0.09	-0.17	-0.07	0.15	0.01	0.02	-0.02	0.21	0.01	-0.12	-0.02	0.13	-0.09	-0.16
$E_B * Q_{DCRP}$	0.13	-0.14	0.06	-0.27	0.02	-0.07	-0.03	-0.15	-0.07	-0.20	-0.11	0.05	-0.14	-0.27	-0.16
$E_A * E_B * Q_{DCRP}$	0.08	-0.15	-0.02	-0.34	-0.21	0.27	0.30	-0.01	0.23	0.05	**0.44***	-0.16	0.07	0.04	0.06
AIC	236.98	263.84	243.63	331.48	286.40	259.03	241.36	76.51	222.75	260.79	209.67	288.42	240.04	226.09	216.56

*Note: β = standardized beta weights. * indicates $p < .05$. ** indicates $p < .01$. ***indicates $p <.000$. p-values were corrected in the full model by Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). EA=Extraversion participant A, EB=Extraversion participant B. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled. M1= Inclination for communication; M2= Using partner's behavior as a guide for own behavior; M3= Attempts to lead the conversation; M4= Feeling self-conscious during the conversation; M5= Conversation seemed awkward, forced and strained; M6= Conversation seemed smooth, natural, and relaxed; M7= Conversation felt involving; M8= Felt put down, patronized or rejected by partner; M9= Felt accepted and respected by partner; M10= Desire to interact more with partner in the future; M11= Enjoyment of the interaction; M12= Tried to accommodate to fit in partner's behavior; M13= Felt comfortable around the partner; M14= Liked conversation partner; M15= Perceived partner as empathic and understanding. Q_{DCRP}= Quotient of Diagonal Cross Recurrence Profile (balance in leader-follower dynamics).*

Table S.4. General Linear Models predicting Perception of the Interaction variables from RR_{LoS} and Agreeableness. Ni=100 participants

	M1.	M2.	M3.	M4.	M5.	M6.	M7.	M8.	M9.	M10.	M11.	M12.	M13.	M14.	M15.
Predictor	β	β	β	β	β	β	β	β	β	β	β	β	β	β	β
Intercept	**0.02*****	**0.00*****	**-0.05*****	**-0.01*****	**0.00*****	**-0.00*****	**0.02*****	**-0.01*****	**0.01*****	**0.06*****	**0.03*****	**0.04*****	**0.03*****	**0.04*****	**0.01*****
(A_A)	0.01	0.10	0.07	-0.18	-0.15	-0.00*	0.01	-0.21	0.08	-0.07	0.04	-0.09	0.13	0.05	-0.02
(A_B)	0.01	0.06	-0.28	-0.03	-0.11	-0.03	-0.16	-0.08	-0.15	-0.02	-0.19	0.04	-0.08	-0.24	-0.29
RR_{LoS}	-0.03	-0.10	0.05	-0.09	0.06	-0.16	**-0.33***	-0.16	-0.12	-0.13	-0.10	-0.07	-0.05	-0.13	-0.17
A_A * A_B	-0.15	0.01	0.12	-0.03	0.09	-0.12	-0.15	0.15	-0.05	-0.14	-0.18	-0.13	-0.15	-0.16	-0.16
A_A * RR_{LoS}	-0.05	0.04	-0.08	-0.08	0.28	**-0.35***	-0.09	0.19	-0.05	-0.09	-0.16	0.20	-0.13	-0.05	-0.13
A_B * RR_{LoS}	0.07	-0.10	-0.04	-0.09	0.06	-0.07	-0.10	0.16	0.13	0.17	0.06	-0.24	-0.03	0.02	-0.16
A_A * E_B * RR_{LoS}	-0.21	0.10	-0.09	-0.01	-0.16	0.15	0.09	-0.20	-0.10	0.15	-0.01	0.17	0.14	0.01	-0.02
AIC	235.92	267	241.39	337.99	284.94	269.32	236.30	59.12	232.79	261.15	224.21	285.08	242.86	232.40	211.15

*Note: β = standardized beta weights. * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p-values were corrected in the full model by Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). EA=Extraversion participant A, EB=Extraversion participant B. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled. M1= Inclination for communication; M2= Using partner's behavior as a guide for own behavior; M3= Attempts to lead the conversation; M4= Feeling self-conscious during the conversation; M5= Conversation seemed awkward, forced and strained; M6= Conversation seemed smooth, natural, and relaxed; M7= Conversation felt involving; M8= Felt put down, patronized or rejected by partner; M9= Felt accepted and respected by partner; M10= Desire to interact more with partner in the future; M11= Enjoyment of the interaction; M12= Tried to accommodate to fit in partner's behavior; M13= Felt comfortable around the partner; M14= Liked conversation partner; M15= Perceived partner as empathic and understanding. RR_{LOS}= Recurrence rate across the line of synchrony (lag-zero).*

Table S.5. General Linear Models predicting Perception of the Interaction variables from LAM_{ARD} and Agreeableness. Ni=100 participants

	M1.	M2.	M3.	M4.	M5.	M6.	M7.	M8.	M9.	M10.	M11.	M12.	M13.	M14.	M15.
Predictor	β	β	β	β	β	β	β	β	β	β	β	β	β	β	β
Intercept	**0.04*** **	**0.03*** **	**-0.03*** **	**0.01*** **	**0.00*** **	**-0.01*** **	**0.03*** **	**-0.02*** **	**0.01*** **	**0.04*** **	**0.03*** **	**0.06*** **	**0.00*** **	**0.03*** **	**0.03*** **
(A_A)	-0.05	-0.02	0.05	-0.24	-0.13	-0.02	-0.02	-0.18	0.09	-0.11	0.01	-0.15	0.17	0.01	-0.05
(A_B)	-0.01	-0.11	**-0.33***	-0.09	-0.09	-0.02	-0.19	-0.06	-0.11	-0.04	-0.20	-0.10	-0.04	-0.26	-0.32
LAM_{ARD}	0.05	0.14	-0.05	0.08	-0.16	**0.28***	**0.29***	-0.13	0.13	0.16	**0.31***	0.04	0.13	0.23	0.19
A_A * A_B	**-0.08***	0.35	0.19	0.13	0.03	-0.08	0.00	0.11	-0.11	-0.10	-0.18	0.13	-0.25	-0.12	-0.02
A_A * LAM_{ARD}	-0.09	-0.02	0.18	-0.03	-0.19	0.16	-0.06	0.06	0.00	0.05	0.12	-0.13	0.12	-0.02	-0.06
A_B * LAM_{ARD}	0.11	**-0.33***	-0.15	-0.04	0.12	0.00	-0.04	-0.05	0.07	-0.14	-0.06	-0.21	0.05	0.02	0.02
A_A * A_B * LAM_{ARD}	0.16	**0.27***	0.14	0.16	-0.02	0.00	0.04	0.04	-0.05	-0.03	-0.02	0.16	-0.13	0.01	0.10
AIC	233.45	257.16	236.10	336.32	284.15	266.41	238.16	71.53	234.65	262.27	214.62	286.97	240.93	228.46	210.98

*Note: β = standardized beta weights. * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p-values were corrected in the full model by Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). EA=Extraversion participant A, EB=Extraversion participant B. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled. M1= Inclination for communication; M2= Using partner's behavior as a guide for own behavior; M3= Attempts to lead the conversation; M4= Feeling self-conscious during the conversation; M5= Conversation seemed awkward, forced and strained; M6= Conversation seemed smooth, natural, and relaxed; M7= Conversation felt involving; M8= Felt put down, patronized or rejected by partner; M9= Felt accepted and respected by partner; M10= Desire to interact more with partner in the future; M11= Enjoyment of the interaction; M12= Tried to accommodate to fit in partner's behavior; M13= Felt comfortable around the partner; M14= Liked conversation partner; M15= Perceived partner as empathic and understanding. LAM_{ARD}= Laminarity absolute relative difference (asymmetries in nonverbal interactional dominance).*

Table S.6. General Linear Models predicting Perception of the Interaction variables from Q_{DCRP} and Agreeableness. Ni=100 participants

	M1.	M2.	M3.	M4.	M5.	M6.	M7.	M8.	M9.	M10.	M11.	M12.	M13.	M14.	M15.
Predictor	β	β	β	β	β	β	β	β	β	β	β	β	β	β	β
Intercept	**0.02*** **	**-0.02*** **	**-0.07*** **	**-0.01*** **	**0.01*** **	**-0.01**	**0.01*** **	**-0.03*** **	**0.01*** **	**0.05*** **	**0.04*** **	**0.01*** **	**0.04*** **	**0.04*** **	**0.02*** **
(A_A)	-0.04	0.08	-0.07	-0.19	-0.14	-0.02	0.02	-0.21	0.08	-0.03	0.04	-0.12	0.18	0.07	0.01
(A_B)	-0.01	0.03	-0.37	-0.04	-0.11	-0.02	-0.15	-0.10	-0.15	0.02	-0.16	-0.03	-0.03	-0.20	-0.27
Q_{DCRP}	0.01	0.07	-0.14	-0.07	-0.17	0.20	0.06	-0.08	0.05	0.07	0.05	-0.01	0.03	0.07	-0.02
A_A * A_B	-0.09	0.13	**0.17***	-0.06	-0.00	0.01	0.02	0.25	0.05	-0.22	-0.12	-0.03	-0.20	-0.17	-0.03
A_A * Q_{DCRP}	-0.02	0.07	-0.03	-0.15	0.15	-0.12	0.02	0.07	-0.01	-0.11	0.02	0.12	-0.04	0.04	0.03
A_B * Q_{DCRP}	-0.10	-0.05	**-0.34***	-0.11	-0.07	-0.02	0.04	0.16	0.14	0.10	0.03	-0.14	0.02	-0.05	0.05
A_A * A_B * Q_{DCRP}	-0.20	-0.13	**-0.32***	-0.07	0.08	-0.15	-0.11	-0.11	-0.10	0.15	-0.03	0.13	0.15	0.04	-0.06
AIC	236.52	266.75	226.98	337.28	285.71	272.96	244.81	69.39	234.697	261.84	226.28	287.57	243	233.07	216.13

*Note: β = standardized beta weights. * indicates $p < .05$. ** indicates $p < .01$. ***indicates $p <.000$. p-values were corrected in the full model by Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). EA=Extraversion participant A, EB=Extraversion participant B. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled. M1= Inclination for communication; M2= Using partner's behavior as a guide for own behavior; M3= Attempts to lead the conversation; M4= Feeling self-conscious during the conversation; M5= Conversation seemed awkward, forced and strained; M6= Conversation seemed smooth, natural, and relaxed; M7= Conversation felt involving; M8= Felt put down, patronized or rejected by partner; M9= Felt accepted and respected by partner; M10= Desire to interact more with partner in the future; M11= Enjoyment of the interaction; M12= Tried to accommodate to fit in partner's behavior; M13= Felt comfortable around the partner; M14= Liked conversation partner; M15= Perceived partner as empathic and understanding. Q_{DCRP}= Quotient of Diagonal Cross Recurrence Profile (balance in leader-follower dynamics).*

Acknowledgments

Acknowledgments

"I am made and remade continually. Different people draw different words from me." — Virginia Woolf, *The Waves*

Completing this PhD has been a very enriching process, and I am deeply grateful to everyone who has supported and accompanied me along the way. The PhD came with some challenges, particularly when I had to face the COVID-19 outbreak just two months after starting, which not only kept me far from home and my family but also delayed my project. Despite the adversity I encountered, finalizing this process is such a great achievement.

First, I would like to express my sincere and deep gratitude to my supervisors: ***Ralf Cox, Saskia Kunnen,*** and ***Ramón D. Castillo.*** Your guidance, expertise, and support have been fundamental in shaping my research and helping me reach this milestone. It has been a privilege to work under your supervision. Thank you for co-creating this project with me.

Ralf, from the moment we first spoke, you were incredibly kind, warm, and helpful. Every conversation with you was unique and insightful. Your intellect, originality, creativity, and integrity have always been a source of inspiration for me. You have been a caring and generous supervisor, offering hope and optimism in moments of uncertainty, and boosting my self-confidence and sense of agency when everything was uncertain. You taught me to think within the framework of complexity science, which has contributed to how I view the world—understanding that behavior, interpersonal dynamics, and the human mind are undeniably complex, requiring innovative approaches to study them. Thank you for introducing me to the community of ecological psychology. While I still have much to learn, the project you helped me materialize has been a fascinating and enriching experience. I am honored to be the first PhD student to graduate under your role as first promotor. And, I am certain we will continue collaborating in the future.

Saskia, thank you for your kindness, wisdom, and unwavering support. I admire the warmth and energy you bring to every interaction, as well as your thoughtful communication style. Your guidance, commitment, and insightful feedback provided me with fresh perspectives on my work. I am especially grateful that you took on the co-supervision of my PhD, even as you prepared for retirement. Your candid and understanding nature has been invaluable to me, and I wish you all the best in your well-deserved retirement and future adventures.

Ramón, we have known each other for more than a decade, and I can confidently say that without your influence, I may not have pursued a PhD in Groningen. Working in your lab and learning about complexity science and experimental research during my undergraduate years was a formative experience. I am deeply appreciative of your support, availability, and generosity throughout this process, especially during our discussions, which greatly improved the rigor of my work. I look forward to our continued academic collaboration in the future. I believe our academic relationship is a fascinating example of how life choices lead to unexpected and complex outcomes.

I would also like to extend my sincere thanks to my co-authors ***Bertus Jeronimus, Zuzanna Laudańska, Przemysław Tomalski,*** and ***Joanna Duda-Goławska***. Your collaboration, insights, and dedication have contributed greatly to the success of this work, and I am grateful for the opportunity to have worked alongside you.

Bertus, thank you for your kindness, encouragement, sincere feedback, and for the conferences we attended together and the symposium we shared. I enjoyed working with you and sharing our mutual interest in personality research. It was a pleasure to collaborate on this project. I am really grateful for your honesty, willingness to always help in any way you could, and always being so caring. I look forward to continuing collaborating!

Zuzanna, thank you for your friendship and academic collaboration. I feel fortunate to have met you, shared an office with you, and enjoyed fun moments during your stay in Groningen. Thank you also for inviting me to the conference you organized in Warsaw with Przemek. You are such an intelligent person, and I feel privileged to work in a paper with you. I appreciate your generosity in sharing your knowledge.

My sincere appreciation goes to the members of my assessment committee—***Marijn van Dijk, Wolfgang Tschacher,*** and ***Theo Klimstra***—for agreeing to be part of this process, especially during the summer. I greatly admire your work, and it is an honor to have you on my PhD promotion committee. Your thoughtful evaluation and constructive feedback have significantly enhanced the quality of my thesis. Thank you very much.

A special acknowledgment to ***Mark Span*** for your technical support throughout this project. Your expertise was invaluable in overcoming the technical challenges I encountered during the lab studies. I deeply appreciate our sincere conversations, your patience, flexibility, creative solutions, and, above all, the kindness and warmth you have shown me.

Thanks to Professor Ezequiel Di Paolo, for being an inspiration in my work and for the insightful email exchanges that helped me rethink some of the initial ideas in the theoretical chapter of this thesis.

To all my ***(former) colleagues, professors, and staff in the Department of Developmental Psychology*** at the Heymans Institute, thank you for fostering an academic environment that contributed to my growth as a researcher. Special thanks to ***Gemma,*** thank you all the conversations, laughs, coffee dates, dog walks, and especially for your friendship over the years which I am sure will last lifelong. I admire your commitment to your research, hardworking mindset and creativity. I am grateful to have you in my life. ***Solomiia*** thanks for your unique, sincere, sweet, and generous friendship. I look forward to seeing you accomplish all your goals in life and being there to celebrate with you. Your friendship has been a precious gift. I truly admire your resilience, and I am sure we will be lifelong friends. ***Hanneke***, thank you for all the conversations and for your help—I'm so happy to see you flourishing in your career. ***Marije***, I enjoyed our trip to Warsaw, all the conversations and laughs. I loved meeting you and I'm sure you will have a very successful PhD. ***Anne Margit***, thanks for all our long walks, deep conversations, music exchanges, and happy evenings; your transparency and friendship have been a great gift. ***Lisette,*** thank you for your generosity, help, and kindness—I admire your creativity, positivity, commitment, and hard work. I hope we can talk more about science and collaborate in the future. ***Niklas***, thank you for your positivity, and conversations; I am looking forward to attending your defense! ***Laura***, thank you for our exchanges of ideas and for inviting me to the book club to talk about ecological psychology. Thanks also to ***Lisa-Maria*** and ***Hector***, I enjoyed sharing the lab with you, and Lisa, thanks for the nice talks and the lovely trip we shared to Trondheim. Thanks to ***Yannick*** for supporting me when starting my experiments and published my first paper. Thanks to the first work roommates I had in the department, ***Joske, Hugh,*** and ***Tai.*** Special thanks to ***Lucia*** and ***Erica*** for your constant kindness and help. Also, I would like to mention the very last PhD fellows I shared office with, ***Oliver*** and ***Nan***, I am so glad to have met you both, thanks for your kindness, conversations. Oliver, thanks for the reading recommendations. It would be a pleasure to collaborate in the future given our common interests. Once again, thanks to all the professors, former colleagues, and PhD fellows from Developmental Psychology during my time in the department—***Peter, Ruud, Annelieke, Barbara, Mandy, Veroni, Ole, Sem, Koen, Rik, Jannis, Charlotte,*** and ***Marlou*** (apologies if I missed anyone). I especially enjoyed the department research meetings.

I would also like to acknowledge the Mindwise editorial board. ***Jeremy, Brian, Yvonne, Eric, Stephan, Yasin,*** and ***Wouter***, it has been a pleasure working with you.

I would also like to acknowledge ***Christin,*** whose hard work and dedication were fundamental to the success of Chapter 5. I truly enjoyed working with you and getting to know you. I wish you all the best in your future projects. Thanks to ***Tim*** for thinking about the details of my experiments and discussing literature with me during his internship. And thanks to all the participants who kindly participated in this dissertation's studies.

Dear ***Sybren, Sophie,*** and ***Tara***, thank you for making my everyday life brighter, happier, and more enjoyable. I am so grateful for having you by my side throughout this process.

A mi familia: mi ***madre***, ***Rosa***, mi ***padre, José***, mis hermanos ***Catalina*** y ***José Luis***, sobrinos ***Joaquín, Sebastián,*** y ***Juan José***, a mi prima ***Francisca***. Gracias por su cariño y preocupación siempre. También a la familia Elorrieta Rojas, que ha sido parte del inicio de este proceso y de una parte fundamental de mi vida, gracias por su cariño, siempre los voy a tener presente.

Finalmente, a mis amigos y mentores en la vida— ***Sergio, Vyera, Alessandra, Catalina R., Catherine, Jessica, Chiara***— gracias por su amistad y apoyo a la distancia. Cada vez que nos vemos es como si el tiempo no hubiese pasado, gracias por su amistad y cariño. Admiro a cada uno de ustedes por su transparencia, profundidad, fortaleza, perseverancia y actitud hacia la vida. Gracias a las personas que han sido parte de este proceso y que no mencioné.

To all of you and every person I have encountered along the way, I extend my deepest gratitude. Thank you.

Curriculum Vitae

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Nicol Arellano Véliz was born on February 19, 1993, in Talca, Chile. In 2012, she began her bachelor's studies in ***Psychology at the University of Talca, Chile***. During her studies, she was awarded a scholarship to complete a semester abroad at ***Rovira i Virgili University in Tarragona, Spain.*** After completing the 5-year program, she graduated with honors, ranking first in her cohort in 2017, earning her degree in Psychology with a Clinical specialization

During her undergraduate studies, Nicol worked as a research assistant with Dr. Ramón D. Castillo on a project focused on embodied cognition and complex dynamical systems approaches to insight in problem-solving tasks, marking her first formal research experience. Her bachelor's thesis, titled ***"The Relationship Between Cognitive and Affective Components of Theory of Mind and the Dark Triad of Personality in Undergraduate Students,"*** was based on original experimental research.

Nicol completed her clinical internship at the University of Talca's Applied Psychology Center (Centro de Psicología Aplicada, CEPA), where she worked from 2016 to 2017, while also completing training in Eye Movement Desensitization and Reprocessing (EMDR), focusing on trauma and other psychological disorders. She also participated in a program for the assessment and treatment of severe maltreatment in children and adolescents. From 2017 to 2018, she worked at the Regional Hospital of Talca in the adult outpatient psychiatry unit.

In 2018, Nicol was awarded a scholarship from the National Agency for Research and Development (Agencia Nacional para la Investigación y Desarrollo, ANID, Chile) to pursue a ***Research Master's in Behavior and Cognition at the University of Barcelona, Spain***. Her Master's thesis, titled ***"A Systematic Review and Meta-Analysis of the Efficacy of Psychological Interventions for Eating Disorders in Outpatient Settings,"*** was completed under the supervision of Joan Medina Alcaraz. Following this, she received a PhD scholarship from ANID (Chile) to pursue her doctoral studies at the ***University of Groningen, Netherlands***.

Nicol began her PhD in 2019 under the supervision of Dr. Ralf Cox, Dr. Saskia Kunnen, and Dr. Ramón D. Castillo. After four and a half years, she completed her dissertation titled ***"Intrapersonal and Interpersonal Dynamics in Personality Expression: A Complex Dynamical, Enactive, and Embodied Account."*** Her research involved original experimental research conducted at the Heymans Institute for Psychological Science, University of Groningen, and included an international collaboration with Zuzanna Laudańska (Polish Institute for Psychological Science), exploring the relationship between sensorimotor development and temperament in infants.

During her PhD program, Nicol also was a member of Mindwise, a science communication platform at the University of Groningen, as part of the editorial team.

In 2024, she completed additional training in ***Compassion-Focused CBT*** and ***Psychotherapy for Relational Trauma and Attachment Injuries***, as well as a professional diploma in ***Relational Intersubjective Psychotherapy*** at the ***Universidad de Los Andes, Chile***, reflecting a commitment to both scientific research and clinical settings.

Publications and submitted manuscripts related to the dissertation

Arellano-Véliz, N. A., Jeronimus, B. F., Kunnen, E. S., & A. Cox, R. F. (2024). The interacting partner as the immediate environment: Personality, interpersonal dynamics, and bodily synchronization. *Journal of Personality, 92*(1), 180-201. https://doi.org/10.1111/jopy.12828

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