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

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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.

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., 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

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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 $\geq$ 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 (MnL)	The Mean diagonal line length (MnL) 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 MnL indicates irregular dynamics and longer MnL indicates stable and regular dynamics.[3]

Note: * Table adapted from Arellano-Véliz, Jeronimus, Kunnen & Cox (2024). [†] 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).

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 & Daly, 2018) 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, Koppensteiner et al., 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 s 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 $\sim$ 20 s of exposure time for positive affect, neuroticism, and openness to reach similar accuracy; and up to 60 s for agreeableness to achieve the optimal ratio between stimulus exposure and accuracy (Carney et al., 2007; but underpowered). Novel 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., 2024). 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., Barrett, 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' 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 provides information about the dynamic organization of a system (Marwan et al., 2007; Danvers et al., 2020; Shockley, 2005).

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

[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 parts of the session (high-level constraints, see method section for details).

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 Fig. 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 Fig. 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 (Fig. 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 et al., 2007). By doing this, we are essentially measuring the information or uncertainty/certainty associated with these patterns (Leonardi, 2018). 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 Fig. 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 Fig. 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

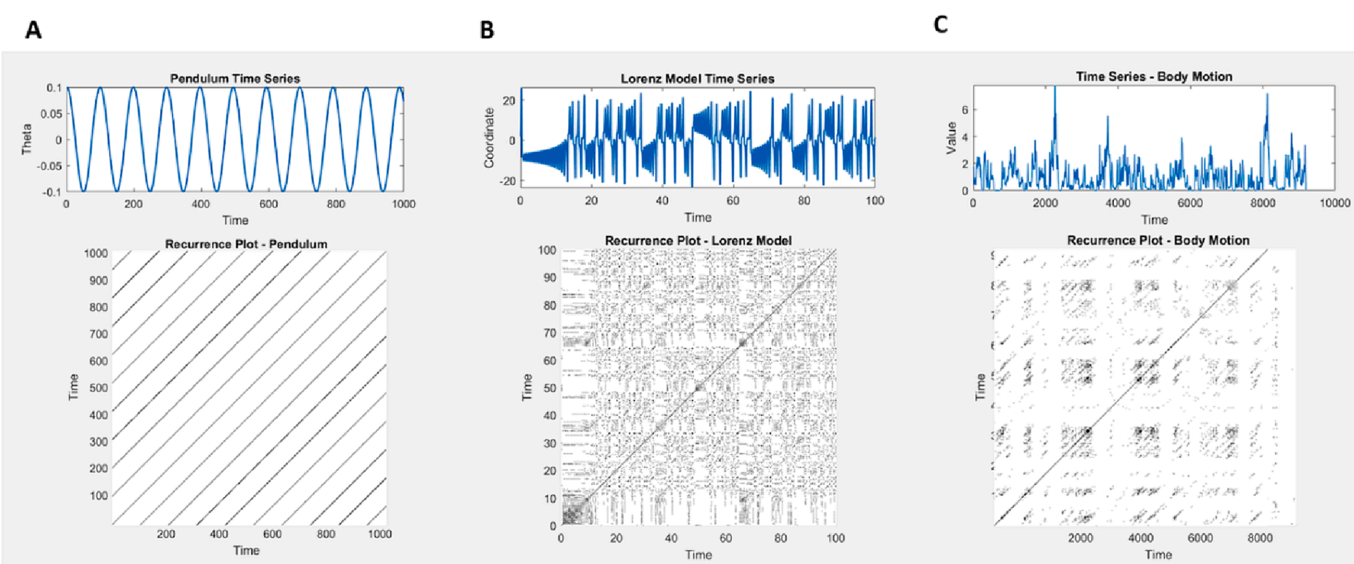

Fig. 1. Examples of different systems' Recurrence Plots Note: The figures illustrate recurrence plots of three distinct systems. In Panel A, we observe the simulated recurrence plot of a simple pendulum oscillation, representing a highly deterministic and patterned system (DET = 0.99, ENT = 0.61, LAM = 0, MnL = 37.84). Panel B displays the recurrence plot of the Lorenz system (DET = 0.64, ENT = 3.71, LAM = 0.88, MnL = 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, MnL = 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).

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 et al., 2007). It provides a global overview of the recurrent patterns and their average duration in the phase space (see Fig. 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 (Fig. 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 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.

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., 2024). 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. 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., 2024). 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 and Costa, 2003). 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., 2020).

2. 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 et al., 2024). Our sample (70 % women, 30 % men,

Table 2
Hypotheses by personality traits and RQA variables.

Variable	DET	ENT	LAM	MnL	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	Negative effects	Negative 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).
Agreeableness	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., 2024) (H2c).
Conscientiousness	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	Negative 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.

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, Clark, & Tellegen, 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 min 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 sub-themes 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?")*.[2] 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., 2024; Paxton & Dale, 2017; Tschacher, Ramseyer, & Koole, 2018) using comparable protocols and task lengths. We measured positive and negative affect (state) pre/post the full task.

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

[2] Protocol of self-referencing topics available at https://osf.io/sbc35/?view_only=e3ecf675b9ce4d3fbd224d8c11a5cb2a.

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 s (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.

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). 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., 2021), '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., 2024).

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 ms (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, 2022; 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., 2020). 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.

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.[3] 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.[4] 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

[3] 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.

[4] 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.

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).

2.6. Power and sensitivity

We used some common effect indicators, the coefficient of determination (R^2), partial eta squared (η^2), correlations (r), and standardized beta weights (β). 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 (η^2) was deemed small (0.01), medium (0.06), and large (0.14) (Cohen & Cohen, 1983). Marginal R^2 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 (β) 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 and 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 Fig. 2 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.

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 bodily perception/sensory life and social-emotional life (topics 2 and 3) predicted more system Determinism, Entropy, Laminarity, and Mean Line compared to introduction (baseline topic 1, see Fig. 3). 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 et al., 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 Fig. 3) 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.

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

Variable	Topic 1. Introduction				Topic 2. Bodily Perception/Sensory Life				Topic 3. Socio-emotional Life				ANOVA
	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 (MnL)	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

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.

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

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.

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, $\beta = .17$, $p < .05$). 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, Fig. 4A). 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.

Neuroticism influenced body motion during the topic about bodily perception/sensory life (topic 2, $\beta = -.23$, $p < .01$) and socio-emotional life (topic 3, $\beta = -.21$, $p < .05$) in terms of system Determinism (see Table 7) and Laminarity (topic 2, $\beta = -.23$, $p < .01$, topic 3, $\beta = -.21$, $p < .05$ see Table 9), and, only when talking about their socio-emotional life (topic 3), in terms of Mean Line ($\beta = -.19$, $p < .05$, see Table 10, Fig. 5). 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.[5] Conscientiousness predicted lower system Determinism ($\beta = -.21$, $p < .05$, Table 7, Fig. 4B) and less Laminarity ($\beta = -.24$, $p < .05$, Table 9, Fig. 4C) 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 = .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) ($\beta = -.27$, $p < 0.05$), 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; $p < 0.001$) 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 ($\beta = -.31$, $p < 0.05$) 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 Fig. 5D), 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 ($\beta = -.33$, $p < .05$, 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 topic), but differences in the other four personality factors influenced how self-referencing topics influenced body motion.

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 ($F_{[1,101]} = 7.50$, $p = .01$, $\eta^2 = 0.07$), 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

[5] 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.

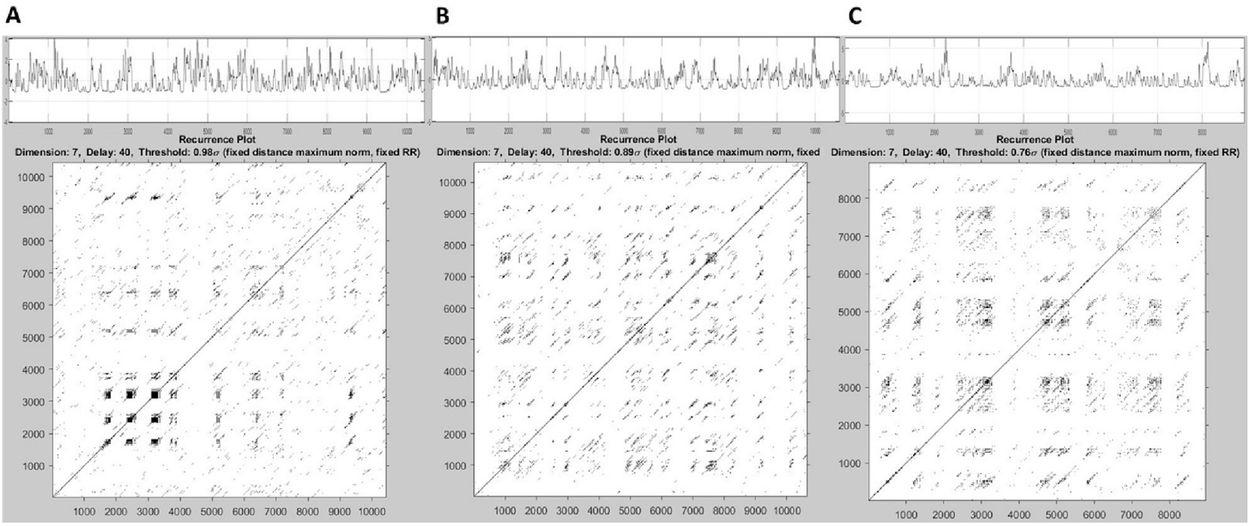

Fig. 2. Recurrence Plots over the three different self-referencing topics Note: The figures represent recurrence plots with the respective time series derived from a participant's RQA in three distinct topics (A = Introduction, B = Bodily perception/sensory life, C = Socio-emotional life. The parameters 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 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 (MnL)	−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. Statistical significance is 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 B (*β*)	Estimate B (*β*)	Estimate B (*β*)	Estimate B (*β*)
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: Statistical significance is 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. Estimate B = unstandardized estimate, *β*= standardized beta weights.

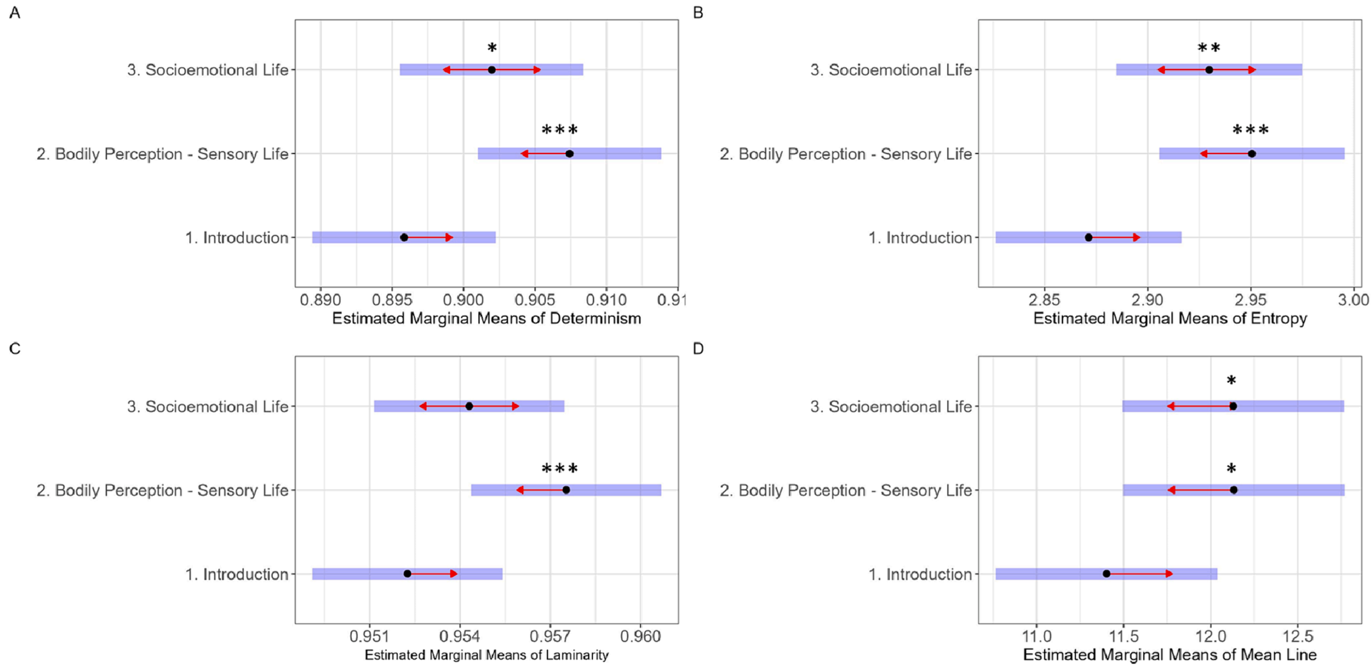

Fig. 3. Plots representing the Estimated Marginal Means by Topic *Note:* Estimated Marginal Means from mixed-effects models by each RQA variable (Introduction was considered the baseline). The self-referencing topics were: 1) Introduction, 2) Bodily perception/sensory life, and 3) Socio-emotional life. *<.05, **<.01, ***<.001.

Table 7
Mixed-effects models predicting Determinism. 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 B (*β*)	Estimate B (*β*)	Estimate B (*β*)	Estimate B (*β*)	Estimate B (*β*)	Estimate B (*β*)
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)
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 (f^2) (marg/cond)	.03/1.68	.03/1.74	.02/1.63	.05/1.65	.04/1.64	0.12/1.81

Note: Statistical significance is indicated as $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. *p*-values were corrected in the full model by Benjamini and Hochberg (1995) procedure . 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. Estimate B = unstandardized estimate, *β*= standardized beta weights.

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

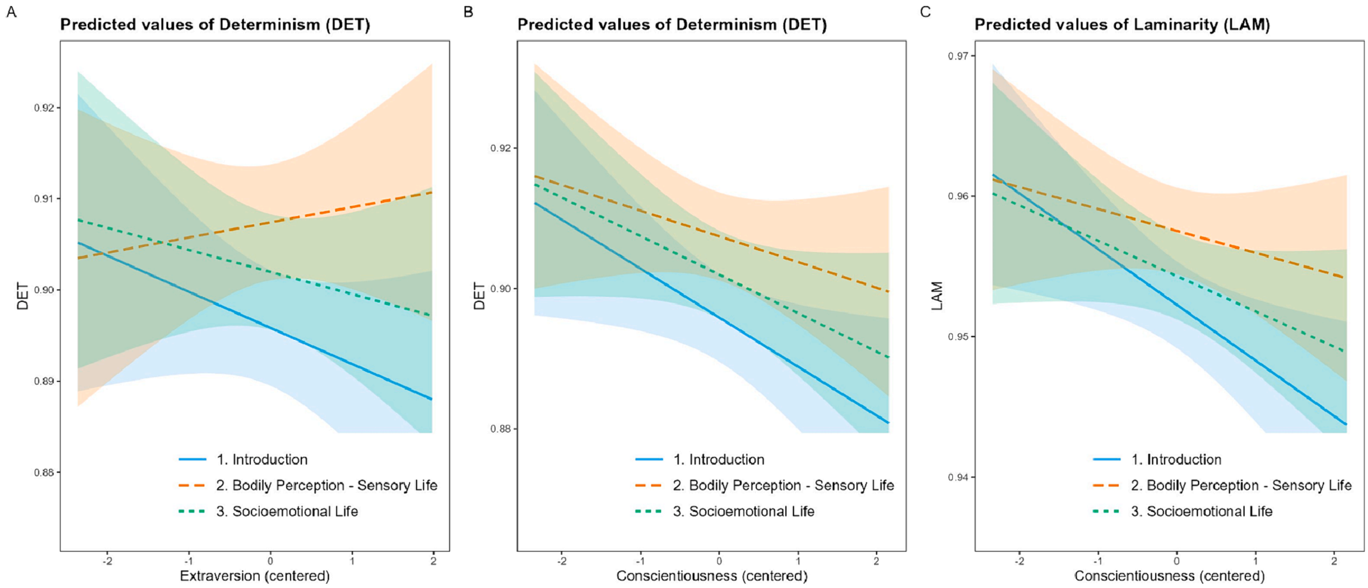

Fig. 4. Plots representing significant fixed effects of Extraversion and Conscientiousness on Determinism *Note:* The figures represent the predicted effects in the individual models of (A) Extraversion on determinism (DET), (B) Conscientiousness on determinism, and (C) Conscientiousness on laminarity (LAM). Personality traits were centered and scaled. Fig. 4A represents the effects of Extraversion on determinism, in this case, the effect of Extraversion * Topic 2 is statistically significant relative to Topic 1 or baseline. Fig. 4B and 4C represent the effects of Conscientiousness on determinism and laminarity respectively which resulted in significant results without interacting with topic.

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 B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)
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)
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: Statistical significance is indicated as $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. *p*-values were corrected in the full model by Benjamini and Hochberg (1995) procedure . 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. Estimate B = unstandardized estimate, *β*= standardized beta weights.

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.

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 B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)
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)
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. R^2/Cond. R^2	.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 (f^2) (marg/cond)	.03/1.74	.03/1.82	.02/1.71	.05/1.74	.03/1.71	.11/1.89

Note: Statistical significance is indicated as $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. *p*-values were corrected in the full model by Benjamini and Hochberg (1995) procedure. 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. Estimate B = unstandardized estimate, *β*= 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 B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)	Estimate B(*β*)
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)
Openness * T.2					.197(.06)	.248(.07)
Openness* T.3					.269(.08)	.592(.18)
Random Effects						
ICC	.51	.51	.51	.51	.50	.50
Marg. R^2/Cond. R^2	.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 (f^2) (marg/cond)	.02/1.08	.03/1.11	.01/1.06	.02/1.07	0.03/1.07	.10/1.17

Note: Statistical significance is indicated as $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. *p*-values were corrected in the full model by Benjamini and Hochberg (1995) procedure. 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. Estimate B = unstandardized estimate, *β*= standardized beta weights.

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

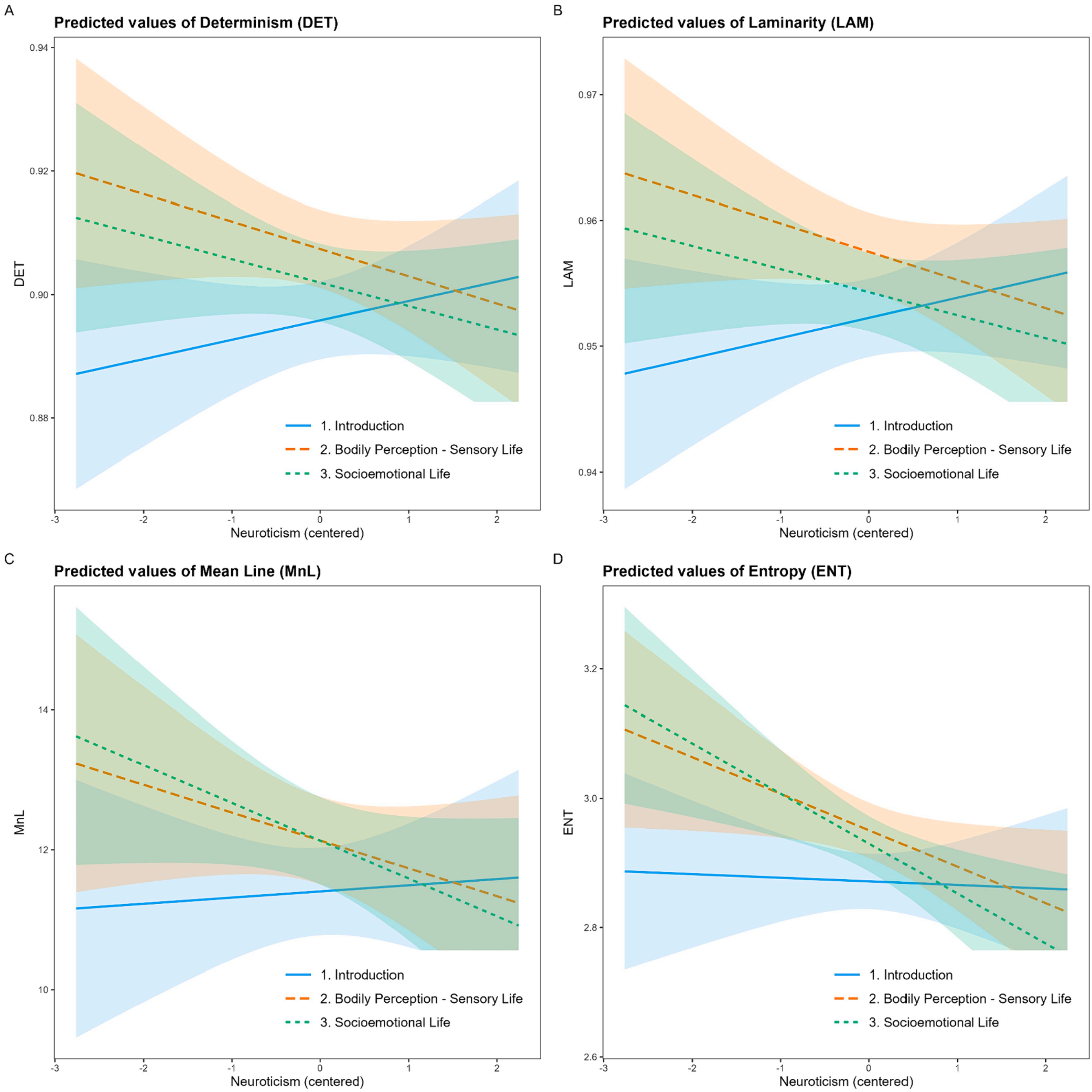

Fig. 5. Plots representing significant fixed effects of Neuroticism on system Determinism, Laminarity, Mean Line, and Entropy *Note:* The figures represent the predicted effects of Neuroticism on determinism (A), Laminarity (B), Mean Line (C) in the individual models; and Neuroticism on Entropy (D) in the full model.

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, 2012; 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.

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: Statistical significance is 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.

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 (DeYoung, 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 not have 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 et al., 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 it 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, 2022) 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.

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.

CRediT authorship contribution statement

Nicol A. Arellano-Véliz: Writing – original draft, Conceptualization, Methodology, Investigation, Funding acquisition, Data curation, Formal analysis, Software, Visualization. **Ralf F.A. Cox:** Conceptualization, Writing – review & editing, Software, Methodology, Formal analysis, Visualization, Supervision. **Bertus F. Jeronimus:** Conceptualization,

Writing – review & editing, Methodology, Supervision. **Ramón D. Castillo:** Conceptualization, Writing – review & editing, Supervision. **E. Saskia Kunnen:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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