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Arellano Véliz, Nicol Alejandra; Cox, R.F.A; Jeronimus, Bertus F.; Guevara, Ramon D.C.; Kunnen, Saskia

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5 authors, including:

Nicol Arellano Véliz

University of Groningen

Ralf F A Cox

University of Groningen

Bertus F Jeronimus

University of Groningen

Ramon Daniel Castillo Guevara

Universidad de Talca

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Arellano-Véliz, Nicol A.[1*], Cox, Ralf, F.A.[1], Jeronimus, Bertus F.[1], Castillo, Ramón D.[2] & Kunnen, E. Saskia[1]

[1]Department of Developmental Psychology, University of Groningen, Groningen, Netherlands

[2]Centro de Investigación en Ciencias Cognitivas, Facultad de Psicología, Universidad de Talca, Chile

*** Correspondence:**

Corresponding Author: n.a.arellano.veliz@rug.nl

Address: Grote Kruisstraat, 2-1, 9712 TS, Groningen, Netherlands.

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Abstract

We explored personality expression through body motion using enactive/complex systems perspectives. We invited 105 adults (aged 18-33, 70% women) to talk for 15-minutes about three self-referencing topics (introduction, bodily perception/sensory life, socio-emotional life). A video frame-by-frame differentiation method provided time-series to perform Recurrence Quantification Analysis (RQA), extracting four measures (Determinism/Entropy/Laminarity/MeanLine). Multilevel models linked Big-Five traits (IPIP-NEO-120) to embodied dynamics. Neuroticism predicted lower determinism and fluctuating dynamics when talking about bodily perception/sensory life and socioemotional life; less complexity and stability when talking about socioemotional life, and post-task negative affect. Extraversion predicted regular/deterministic dynamics when talking about bodily perception/sensory life. Conscientiousness predicted less deterministic and more variability. Agreeableness predicted low post-task negative affect. The results are discussed integrating enactive/complexity, and personality perspectives.

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

1 Introduction

We examine how personality differences are expressed in body motion dynamics when a person speaks in a semi-structured individual laboratory session to study human self-organization in a standardized context. Our research work is grounded on enactive, embodied, and dynamic process perspectives, which can be applied at the level of the cell/organ/organism or extended to more abstract levels of human cognitive and psychological functioning and personality systems (Varela et al., 1991/2017; Carruthers et al., 2005; Di Paolo et al., 2017; Hovhannisyan & Vervaeke, 2022). In the present study, young adults talk about three specific self-referencing topics to examine self-organization dynamics extracted from body motion (question 1), and subsequently, we study whether and which personality differences explain (part of the) variation in measures of dynamic self-organization of body motion (question 2). Our theoretical framework and methodological approach including the operationalization of four dynamic systems measures are outlined below (and in Table 1) before we present and discuss our study results.

From the enactive approach to personality research

Enactive and embodied perspectives describe humans and all other living organisms as self-organizing adaptive systems involved in a non-linear and continuous exchange of energy, information, and matter with their environment (e.g., Di Paolo & Thompson, 2014; Fuchs 2017). The *continuity thesis* in this line of thinking describes a continuum between basic life processes up to emergent psychological functionality such as cognition and meaning that cannot be reduced to a brain or nervous system but emerges from distributed processes throughout the whole organism (Varela et al., 2017; Thompson, 2010; Johnson, 2015; Fuchs, 2020). From this perspective, (a) human physical and mental organization and the material world share a fundamental set of (self-)organized features; and (b) the individual and environment are in a constant mutually constraining interaction (Thompson, 2010; Varela et al., 2017; Galbusera et al., 2019).

This interconnectedness between individuals and their environment shapes human affect, cognition, and behavior, and has been a focus of study across various fields including biological, developmental, personality, and social psychology (Tooby & Cosmides, 1992; Dawkins, 2016; Rauthmann, 2021). The environment in which an individual is situated presents specific opportunities or *affordances*, influencing the likelihood of specific behaviors (Gibson, 1979; Rietveld & Kiverstein, 2014; Bruineberg et al., 2019), thereby establishing nonlinear person-environment interactions (Davis et al., 2016; Schloesser et al., 2019; Bloch et al., 2019). These interactions manifest through nonverbal features such as gaze, gestures, and body motion, requiring coordination (within-subject and with the environment) to achieve self-regulatory and communicative objectives effectively (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). An accepted conceptualization defines personality as an abstraction to describe and explain the relatively stable patterns of what someone feels, thinks, does, and desires over time and situations (Larsen et al., 2020; Wilt & Revelle, 2019). From a dynamic perspective, personality is understood as a system that flexibly adjusts to situations and evolves within humans over their lifespan (Vallacher et al., 2002; Nowak et al., 2020). Each adult with a characteristic level (baseline) on each dimension (an attractor state) around which states fluctuate in response to situational factors and the psychological landscape, which is also known as the dynamic equilibrium model (see Sosnowska et al., 2019). Some enactive and ecological theorists understand personality as stylistic individual differences in their perception of the world ("filters"), as well as their selection, evocation, and creation of environments (e.g., Buss, 1991; Baron & Boudreau, 1987; Satchell et al., 2021). According to these approaches, personality traits would be organized as adaptive cognitive systems to cope with environmental demands (e.g., Mischel and Shoda, 1995; Nettle, 2006; Hovhannisyan & Vervaeke, 2022).

Empirical studies in personality research suggest that 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 ascribe differences in extraversion and neuroticism (emotional stability, see Koppensteiner, 2011, 2013), or differences in dominance, trustworthiness, and competence (Koppensteiner et al., 2016), among others. Similarly, brief glimpses of milliseconds up to seconds of target behavior i.e. *thin-slices* of visual information suffice for many humans to reliably attribute affective states, personality, or other traits and further relevant information to targets (e.g., Ambady & Rosenthal, 1992; Ambady et al., 2000; Jiang et al., 2023).

When it comes to the reliability of discerning specific personality traits, the higher interrater reliability of agreeableness, extraversion, and conscientiousness suggests greater accessibility to observers; whereas neuroticism and openness seem to be more difficult to discern in this set of behavioral snippets (e.g., Albright et al., 1988; Jiang et al., 2023). A meta-analytic study indicated that 30 seconds of exposure time sufficed and more did not notably improve personality judgment accuracy (Ambady & Rosenthal, 1992). Later work noted that observers required five seconds to judge extraversion, conscientiousness, intelligence, and negative affect accurately, but up to 60 seconds to reach this accuracy on neuroticism, openness, agreeableness, and positive affect (Carney et al., 2007). Overall, the methodology of thin-slice behavioral observation suggests that human accuracy in personality observation is situation dependent, such as whether the target is in a dyadic or group situation, which means visual information is enriched with contextual understanding (Jiang et al., 2023). These findings are relevant to the extent that, if minimal observable cues are accurately used to discern attributes from others, we as researchers can find information (i.e., patterns/features) in diverse modalities of measurement that direct us to specific psychological constructs (e.g., traits/states).

Specifically, embodied features –such as body motion over short periods– provide information about personality and other individual differences and can inform observers of self-organizing processes inherent to their individuality. A stable and standardized situation (such as a laboratory setting) may allow for reliable measurements of contextual differences in systems behavior, as evident in body motion dynamics, which are theorized to map individual personality differences. Accordingly, we combine body motion time series with self-reported personality and affect (prior and post-task), which may foster a nuanced and integrative understanding of personality processes as expressed and enacted through embodied features and person-environment interactions.

Complex systems can bridge enaction and personality research paradigms

The convergence of complex systems and enaction principles presents an opportunity to bridge enaction and personality research paradigms (e.g., Fajkowska, 2015). This is achieved by recognizing that dynamics within various modalities (e.g., embodies features) can serve as windows into psychological processes (Thompson & Varela, 2001; Michaels et al., 2021; Xu et al., 2020). Complex systems (e.g., human beings) are composed of interacting elements that result in spontaneous self-organization (Strogatz, 1994; Vallacher et al., 2013; Gallagher & Appenzeller, 1999); enabling the occurrence of emergent behavior and patterns over time (Goodwin, 2001; Pross, 2016; Richardson & Chemero, 2014). It is within this context that we endeavor to capture self-organizing dynamics from body motion patterns, exploring how individual systems respond to diverse environmental constraints and the degree to which personality traits predict variations in motion dynamics.

Dynamic self-organization underlies and maintains stability (Pross, 2016; Varela et al., 2017). Through observable behavioral shifts during *critical states* or phase transitions, the system shifts to a distinct state or "attractor" in response to environmental/individual constraints (Vallacher et al., 2013). In this sense, situational constraints such as a motor task (low-level constraint) or a conversation topic (high-level constraint) can promote adaptation and the emergence of critical states, resulting in novel emergent properties (cf. Bak & Wiesenfeld, 1987; Kelso & Schöner, 1988; Plenz et al., 2021). These emergent properties can be captured at different levels of analysis, for example, in body motion dynamics, as we propose in this study.

Dynamic self-organization can offer insights about individual differences in personality traits stability (e.g., Bleidorn et al., 2022 for trajectories); and critical states can provide information about the responsivity to situational constraints within varying contexts contingent on individual differences (cf. Paxton & Dale, 2017). For example, conscientious individuals (vs. low conscientious peers) are typically conceived as stable over time (e.g., stronger attractor pull; Fetterman et al., 2010). Whereas people high in neuroticism (low emotional stability) might exhibit heightened reactivity to stress and more diverse behaviors across situations (e.g., Xin et al., 2017). Highly extroverted individuals may exhibit consistent movement patterns that embody their inclination for social interactions such as elevated speed of movement, and overall kinetic activity, which shows their dynamic and expressive approach to their surroundings (Luck et al., 2010). These patterns reflect the interplay of self-organization processes across neural, cognitive, musculoskeletal, and social subsystems that underlie personality factors (Buss, 2019).

In sum, enaction theory provides a complementary perspective on the intricate relationship between behavior, personality, and the situation and suggests that personality traits are not merely abstract concepts but embodied and enacted systems that allow for consistent body motion patterns in the interaction with one's environment (e.g., mediated by cognitive processes), in line 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). In this paper, we focus on body motion to examine emergent self-organizing patterns at the level of the whole individual sensorimotor system (Vallacher et al., 2013; Nowak et al., 2020) to see whether we can discern personality differences therein.

Current study

We investigated personality differences as expressed in body motion dynamics when a person speaks individually in a semi-structured task[1], Body motion dynamics were measured during three self-referencing topics to examine individual self-organization (using Recurrence Quantification Analyses, RQA) in terms of system Determinism, Entropy, Laminarity, and Mean Line, and these measures are introduced and defined in Table 1 and our method section.

We hypothesized that (H1) self-referencing topics predict (part of) the dynamic self-organization operationalized by RQA measures (details on statistical significance, effect size, power, and sensitivity are provided in the method section). We further anticipated that personality

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

differences would moderate the effect of these topics on body motion dynamics (H1b), drawing from research on the influence of conversational constraints *(high-level constraints)* on behavior (Abney et al., 2014; Paxton & Dale, 2017; Tschacher et al., 2018; Arellano-Véliz et al., 2023).

In the context of our RQA measures, we reasoned that adaptable sensorimotor systems exhibit complexity and stability (De Jonge-Hoekstra et al., 2020). Complexity arises from the interplay of information and (dis)equilibrium, fostering a functional, flexible, and adaptive state (López-Ruiz et al., 1995). Thus, systemic stability through self-organization should be reflected by complexity (positive effects on Entropy), regularity (positive effects on Laminarity), stability (positive effects on Mean Line), and predictability (positive effects on Determinism; Manor et al., 2010; Galbusera et al., 2019). 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:

Extraversion as 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), and high scorers were expected (H2a) to show adaptive self-organizing behavior as indicated by more system Entropy (complexity/flexibility), Determinism, Laminarity, and Mean Line. Neuroticism captures more unstable patterns of body motion (Koppensteiner, 2013) and emotion dynamics (Mader et al., 2023). Neuroticism was expected (H2b) to associate with less adaptive dynamic self-organization than other traits, thus lower system Entropy, Laminarity, Determinism, and Mean Line. High Agreeableness was expected (H2c) to predict adaptive dynamic self-organization evidenced by more complex/flexible patterns of movement as indicated by more system Entropy (cf., Arellano-Véliz et al., 2023), Determinism, Laminarity, and Mean Line. Conscientiousness captures orderliness and prioritizing non-immediate goals (DeYoung, 2015), anticipated to be reflected in organized/controlled movement patterns, thus in stronger system Mean Line and Determinism (H2d). High openness to experience is associated with body motion direction and variability (e.g., Koppensteiner, 2013) and dyadic attunement (synchronization, see Tschacher & Ramseyer, 2018); therefore we predicted (H2e) more complex/flexible patterns of movement as reflected in higher Entropy and lower Determinism (predictability), which may be linked to behaviors of exploration and novelty (Gocłowska et al., 2019). All general predictions were pre-registered. In addition, affect valence pre and post-task were explored as a process (self-report) measure in connection to dynamic self-organization and personality.

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. A total of 105 undergraduate students, from a total of approximately 300 screened students (age range 18-33, mean = 20.48, *SD* = 2.6) took part in a laboratory session (same screened sample as in Arellano-Véliz, 2023). Our sample (70% women, 30% men, 0% other) came from diverse backgrounds (50% Dutch, 26%, German, and 24% other). This study was approved by the Ethical Committee for research with human participants of the Faculty of Behavioural and Social Sciences, University of Groningen, Netherlands.

2.2 Self-report

2.2.1 Personality traits

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

2.2.2 Affect Valence (process assessment)

Positive and negative affect states were measured with the 10-item self-report I-PANAS-SF instrument (Thompson, 2007) that was assessed 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) a 5-point Likert scale from 1 (very slightly) to 5 (extremely). Composite scores for positive affect (PA) and negative affect (NA) were calculated by summing the item scores. The psychometric properties of the I-PANAS-SF were comparable to the original 20-item PANAS, with high correlations for both PA (r = 0.92) and NA (r = 0.95, both $p < .01$; Thompson, 2007). The I-PANAS-SF demonstrated adequate test-retest reliability (N = 143, r = 0.84 for both PA and NA, $p < .01$) and good internal consistency, with Cronbach's alpha coefficients ranging from 0.72 to 0.78 (Thompson, 2007), which are similar to those of the original 20-item PANAS version (Watson et al., 1988).

2.3 Procedure

When the participants arrived at the laboratory, they were asked to read the informed consent and to wear a heart rate belt (not reported in this paper). Participants were instructed to speak in front of a camera about themselves for 15 minutes on three broad and increasingly personal topics. They were standing on a posture tracking board (data not reported in this paper), which also served as a marker for the exact position to be recorded. The experimenter (female) stayed in the same room behind a screen to not disturb the participants. The participants were asked to talk as openly and freely as they wanted about themselves as if they were speaking to someone who did not know them. The topics were defined as follows: 1) Introducing oneself; 2) bodily perception/sensory life; 3) socio-emotional life. Some guiding questions or subthemes were given together with the instructions in case they needed some directions, for example, for topic 1: *"what is your name and age?"*, "*how does a normal day look like for you?";* topic 2: *"How would you describe the way your body feels when you move? (e.g., you feel it graceful, heavy, light, energized, tired)";* topic 3: "*How do you describe your childhood and family life?"; "How would you describe yourself emotionally?"*. These guiding questions were given as suggestions, and the requirement was to speak for approximately five minutes on each of the main three broad topics. The topics represent different perspectives and high-level constraints for self-referencing and elaborating on each individual's personal experiences. 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 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 files were preprocessed within time windows of 0.5 seconds (smoothed) and standardized using the *SD* (rescaled). 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 Dynamic Self-Organization Operationalizations via *Recurrence Quantification Analysis*

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. RQA is a nonlinear time series analysis that produces robust results with few assumptions and provides information about the dynamic organization of the system under study (Shockley et al., 2022). The four measures of dynamic self-organization we extracted were differences in Determinism, Entropy, Laminarity, and Mean Line, which we define and describe (also statistically) in Table 1. The RQA uses the number and duration of recurrences within the system's multidimensional phase space as visualized in recurrence plots that provide a two-dimensional representation of a multidimensional phase space trajectory and are depicted in a symmetrical square matrix with a time series repeated in both *x* and *y* axes (Webber & Zbilut, 2005; Marwan et al., 2007; Konvalinka et al., 2011). RQA reduces the complexity of multidimensional data to a more comprehensible two-dimensional representation. In the context of our study, a person's movement while talking about different themes is a multidimensional system affected by an unknown number of variables, and personality traits can be seen as part of those variables.

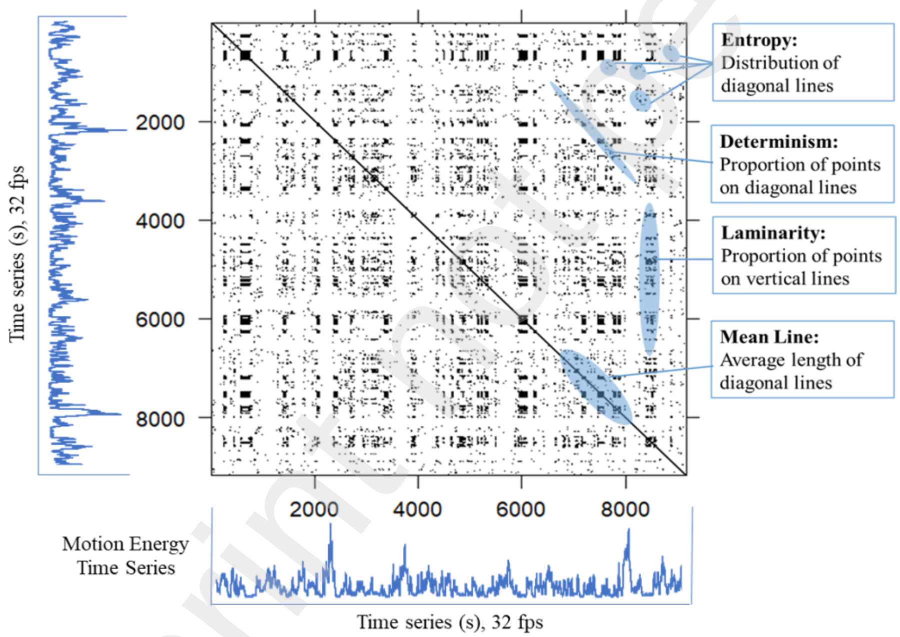
The visualization of state recurrences such as in Figure 1 provides these states at the time "*i*" with respect to a different time "*j*" to create a pattern in a square matrix composed of ones and zeros (or black and white dots in a plot). Both axes of the matrix (time axes) represent the movement system's temporal 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 state changes that repeat over certain trajectories or different times, and these patterns can provide valuable 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 gradually (Spiegel et al., 2016; Tomassini et al., 2022). Vertical lines are also an indication of laminar states (Marwan et al., 2007). RQA relies on the concept of informational entropy (Shannon, 1948) to quantify the amount of uncertainty or randomness present in the system. Informational entropy measures the level of unpredictability or disorder in the state transitions within the recurrence plot (Marwan, 2007). The graphical information enables us to extract insights from the state recurrences and the underlying system dynamics to enrich the interpretation of the numerical measures extracted from the RQA. All dynamic measures and their interpretations are outlined in Table 1.

A distinctive feature of RQA and recurrence plots are their reliance on the sequential organization of the time series under investigation. Conventional measures of central tendency discard the small-scale temporal order information in the data when they aggregate information derived from the system's behavior (e.g., mean, SD, MSSD, see Webber & Zbilut, 2005). A growing body of evidence showed this temporal information to be crucial to predict and understand better human bodily and mental functioning (e.g., Kunnen, 2012; Box-Steffensmeier et al., 2014; Michaels et al., 2021). We computed central tendency measures in order to compare both linear (central tendency) and nonlinear (RQA) measures over the different self-referencing topics of the study.

The time series used for RQA were preprocessed, thus smoothed, rescaled, and cleaned. The parameters for the phase state reconstruction (lag and embedding dimension) were set to the values:

lag = 40, embedding dimension = 7, following the procedure previously described in the literature (e.g., Wallot & Leonardi, 2018; Wijnants et al., 2012), and employed previously in this dataset (Arellano-Véliz et al., 2023). In the present study, we set the minimum line length to the value of *lmin* = 4, which is equivalent to four consecutive points that conform diagonal lines in the recurrence plot, setting a threshold for short time scales at 120 milliseconds (0.12s, similar to Tomassini et al., 2022). The default value used in the literature is *lmin* = 2, however, several studies have tried different values of *lmin* to decrease the likelihood to find random structures in diagonal lines in diverse complex systems (e.g., Thiel et al., 2002; Tomassini et al., 2022; Sviridova & Ikeguchi, 2022). Importantly, the parameter definition will depend on the type of system and processes under study. We used a fixed recurrence rate of 2% for all participants instead of a prespecified radius, accounting for an improvement in the reliability and comparability of our results across conditions (e.g., Konvalinka et al., 2011; Wijnants et al., 2012; van den Hoorn et al., 2020). See *Figure 1* for a representation of a recurrence plot and our variables of interest.

Figure 1. Recurrence Plot



Note: This is the RQA plot of one participant during self-referencing topic 3 when talking about socio-emotional aspects of their life. The *x* and *y* axes represent the repeated time series at a sample rate of 32 fps. The dynamic measures are defined and explained in Table 1. Figure layout and labels were adapted from Coco et al., (2017), Webber & Zbilut (2005), and Arellano-Véliz et al. (2023). The parameters used were: lag = 40, embedding dimension = 7, lmin = 4, RR = 2%. The plot was created on Rstudio using the 'nonlinearTseries' package (García, 2022).

—Table 1–

2.5 Multilevel Linear Mixed-Effects Models

Big Five personality traits were associated with dynamic self-organization measures of body motion (using RQA) across three self-referencing topics using 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, level 1, N_1= 315) were nested into the "participant" structure level where personality traits were situated (level 2, N_2= 105). Effect size and significance 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), followed by models with each personality trait separately (in interaction with topic) to examine trait-specific effects.[2] Third, we estimated a full model with all personality traits cumulatively predicting each RQA measure (in interaction with topic), resulting in a total of 24 models (four full models) to examine the relationship between the big five personality traits and dynamic self-organization of body motion.

Dependent variables in each model were the dynamic self-organization RQA measures (Determinism/Entropy/Mean Line/Laminarity) and the independent variables were the Big Five personality traits (Extraversion, Neuroticism, Conscientiousness, Agreeableness, and Openness to Experience) and the self-referencing topic (a categorical variable with three levels: 1. introduction; 2. bodily perception/sensory life; 3. socio-emotional life), where the introduction topic was considered the baseline in the models.[3] The models included a random effect (Participant ID) to account for the variation in the response variable that was not accounted for by the fixed effects (i.e., personality traits and topic). All the continuous predictors (personality traits) were centered by their mean and scaled, which involves subtracting the group grand average from each personality score to prevent multicollinearity issues (because of the correlation of predictors), and to improve the interpretability

[2] The short models are defined following the structure: [Determinism ~ (Neuroticism) * Topic + (1|Participant). One model was performed for each personality trait predicting each RQA measure in interaction with the topic.

[3] The full mixed effects models are defined following the structure: [Determinism ~ (Neuroticism + Extraversion + Conscientiousness + Agreeableness + Openness to Experience) * Topic + (1|Participant). One model per RQA measure was performed.

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, namely, the coefficient of determination (R^2), Cohen's *d,* partial eta squared (η^2), correlations (*r*), and partial regression coefficients (β). Henceforth 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). For Cohen's *d* we identify 0.20 as small, 0.50 as medium, and 0.80 as large (Cohen's 1988). Partial eta squared (η^2) was deemed small (0.01), medium (0.06), and large (0.14) (Cohen & Cohen, 1983). And for correlations (*r*) and beta's (β) as small if they are 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), although we are aware that our sample size is modest in the context of personality research. In the present study with a sample size of $N = 105$, the statistical power to detect a medium effect size of Cohen's $d = 0.50$ at alpha = 0.05 was 0.85 (calculated with the "pwr" R package, Champely, 2022), indicating a likelihood of 85% to detect effects of this magnitude (>0.50 SD) if they exist. This applies to all the models of dynamic organization of body motion and personality traits as they have the same structure.

In the full models, we controlled False Discovery Rate by correcting the *p*-values using the Benjamini-Hochberg (1995) procedure. This method consists of a modified Bonferroni correction (usually less conservative) to adjust for alpha inflation related to multiple hypothesis testing (performed with "stats" R package, R Core Team, 2022).

3 Results

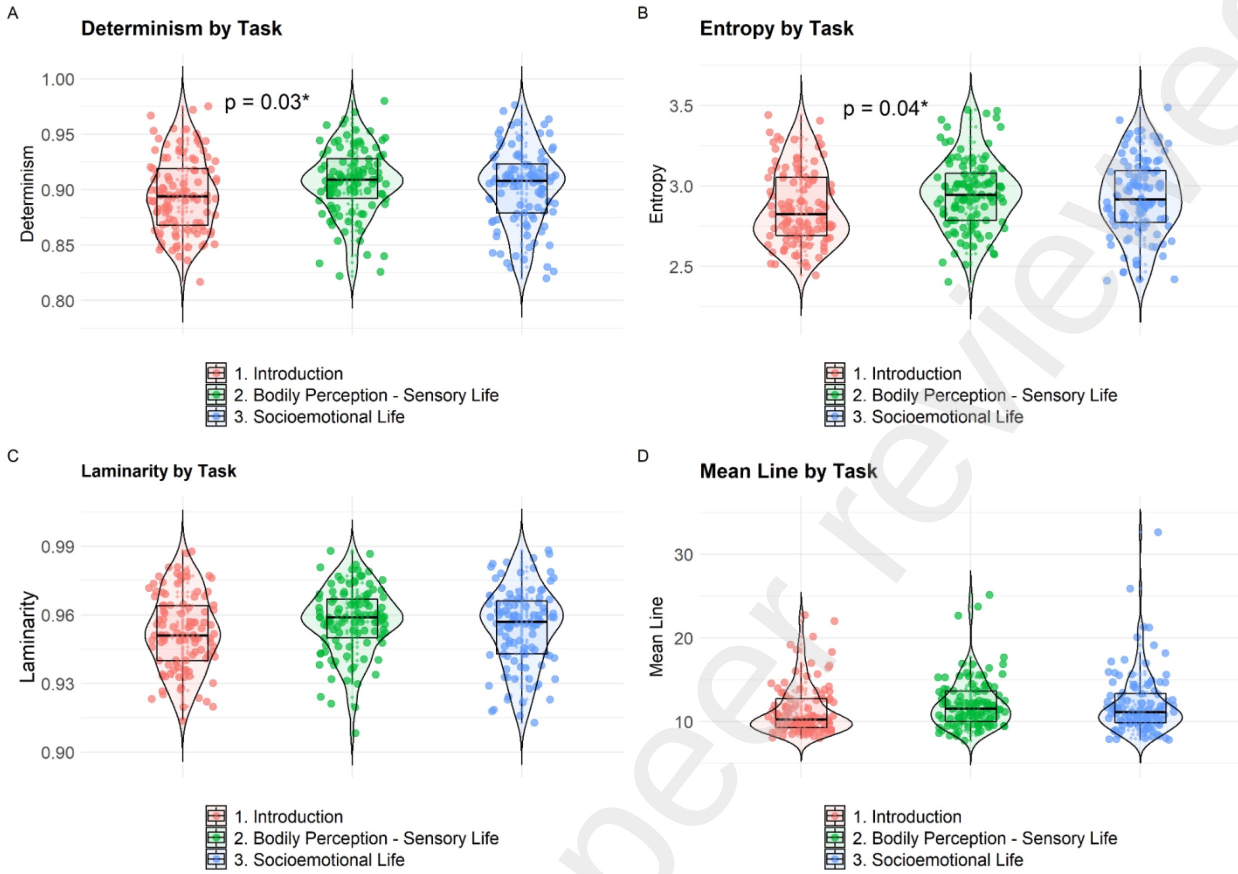
3.1 Dynamic Self-Organization by Self-referencing Topics

The descriptive statistics for the variables of interest per topic (or self-referencing topic) and the self-report measures are provided in Tables 2 and 3. 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 topic 2 and 3 (see Table 2).

A repeated measures Analysis of Variance (ANOVA, see Table 2) 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 ($F_{(2,208)} = 7.602$, $p < .001$, $\eta^2 = .02$), see Figure 2. 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 (topics) on the dynamic self-organization of body motion (H1), but the topic effect was not the same in all RQA measures, as illustrated in the recurrence plots for each topic in Figure 3. 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: $F_{(2, 208)} = 1.65$, $p = .20$, $\eta^2 = .02$).

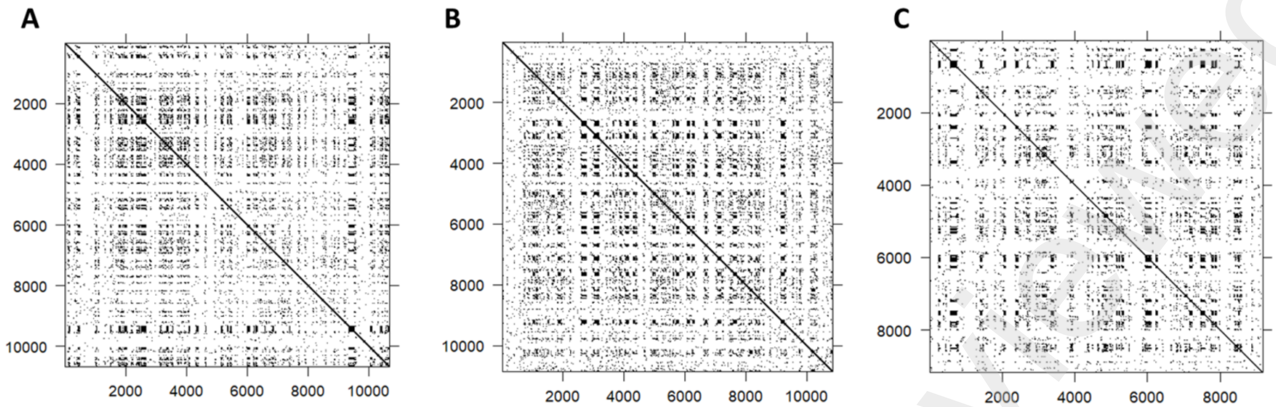
Overall, these findings suggest that the specific self-referencing topic influences their dynamic self-organization of body motion, as captured by RQA measures such as determinism and entropy. However, the topic effect did not extend to all RQA measures in this test and did not influence linear measures of mean body motion and the standard deviation of body motion. This suggests that nonlinear and linear measures do not evidence the same granularity in evidencing systems' dynamics and patterns (i.e., body motion dynamics), as here the nonlinear measures appear to be sensitive to differences in self-referencing topics.

Figure 2. Plots representing the distribution of RQA measures by self-referencing topics



Note: The self-referencing topics were: 1) Introduction, 2) Bodily perception/sensory life, and 3) Socio-emotional life. *p*-values were Bonferroni corrected. Both determinism and entropy were significantly higher during topic 2.

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



Note: The figures represent the recurrence plots from one participant during the three different topics (*A* = Introduction, *B* = Bodily perception/sensory life, *C* = Socio-emotional life. The parameters used were: lag = 40, embedding dimension = 7, *lmin* = 4, *RR* = 2%. Different patterns and trajectories over the topics can be observed. In panel A (topic 1), the cluster structures in the superior left quadrant are less prominent in the rest of the plot (asymmetrical), this pattern can be indicative of changes in the trajectories over the topic; Panel B (topic 2), exhibits a homogeneous and relatively symmetrical repetition of cluster structures (black blocks), suggesting regularity and repetition in the system's dynamics. In panel C (topic 3), the recurrence plot shows less regularity and higher variability over the topic; it is possible to see disruptions (white bands), indicating nonstationarity and transitions (Marwan et al., 2007). Overall, the clusters represent regions in phase space that the system repeatedly visits. The plots were created on Rstudio ('nonlinearTseries', García, 2022).

3.2 Correlation analysis

Pearson correlation coefficients showed positive intercorrelations between all RQA measures (see Table 4). A grand average of each RQA and linear body motion measure among the three different topics was computed into one single value of each measure to compute the correlations. The correlations between RQA and linear measures of body motion and self-reported personality and affect are provided in Table 4 and showed 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). 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 agreeableness with openness (see Table 4). The Big Five dimensions are in principle defined as independent personality factors (orthogonal), nevertheless, these associations are commonly reported, as behavior cannot be clearly divided into absolutely independent categories (Koppensteiner, 2013); and also 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 (a "maturity" process, see Bleidorn et al., 2022).

3.3 Predicting self-organizing dynamics from personality traits

First, the models estimating the effect of topics independent of other predictors on the RQA measures (Table 5) revealed that talking about sensory and social-emotional life (topics 2 and 3) predicted more system Determinism, Entropy, Laminarity, and Mean Line compared to the self-introduction (baseline topic 1). 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). Effect sizes (Cohen's *d*) as presented in Table 5 indicate large effects for the fixed and random effects of these models. The Intraclass Correlation Coefficient (ICC), or proportion of variance explained by each participant or clustering structure (Hox, 2017), here captures the consistency of the observed effects for each individual across topics, the larger the ICC, the higher the consistency of observed behavior over 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.

Personality moderated the topic effects on dynamic system measures (short models), as more extroverted participants showed more determinism when discussing their bodily perception and/or sensory life (topic 2, $p = 0.04$). The conditional R^2 of this model is .64 (percentage of explained variance given by fixed and random effects), thus higher Extraversion scores were associated with more predictable, consistent, and regular movement dynamics (Determinism) when talking about their bodily perception/sensory life (see Table 6, Figure 4A). This supports the higher dynamic self-organization of extraverted individuals (H2a), but note there were no significant effects linked to the other RQA measures, therefore, H2a was partially met. And, as shown in the plot, this effect when 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) and socio-emotional life (topic 3) in terms of system Determinism (p< 0.05, conditional R^2 = .64, see Table 6) and Laminarity (p< 0.05, conditional R^2 = .64, see Table 8), and, only when talking about their socio-emotional life (topic 3), in terms of Mean Line (p< 0.05, conditional R^2 = .53, see Table 9 and Figure 5). These results suggest that higher neuroticism scores were associated with less predictable, less deterministic system processes, and less laminar states (more variability, fluctuation, and volatility), and less stability in topics 2 and 3. These results support our hypothesis about lower emotional stability (high neuroticism) and the critical effects related to the topic (H2b).

Agreeableness showed no association with system states nor any interaction with the topic in any of the individual models, as 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 (H2c not supported). Conscientiousness predicted lower system Determinism (p = 0.03, conditional R^2 = .62, Table 6, Figure 4B) and less Laminarity (p= 0.01, Table 8, Figure 4C), but no interaction with the self-referencing topic, thus main-effects only. More conscientious participants showed less deterministic (predictable), 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 interacted with the self-referencing topics.

When performing the full models, the effect of personality traits on determinism (full model, see Table 6 model 6), exhibited statistically significant results (□ = 0.91, p<.001, conditional R^2 = .64). When talking about bodily perception/sensory life participants showed higher values of determinism (“predictability”) in comparison to their introduction of themselves. Neuroticism (emotional stability) showed interactions with the topic socio-emotional life (topic 3), particularly, more neurotic participants showed lower determinism (predictability) (p < 0.01), in keeping with the effects observed in the short model of neuroticism-determinism, supporting H2b.

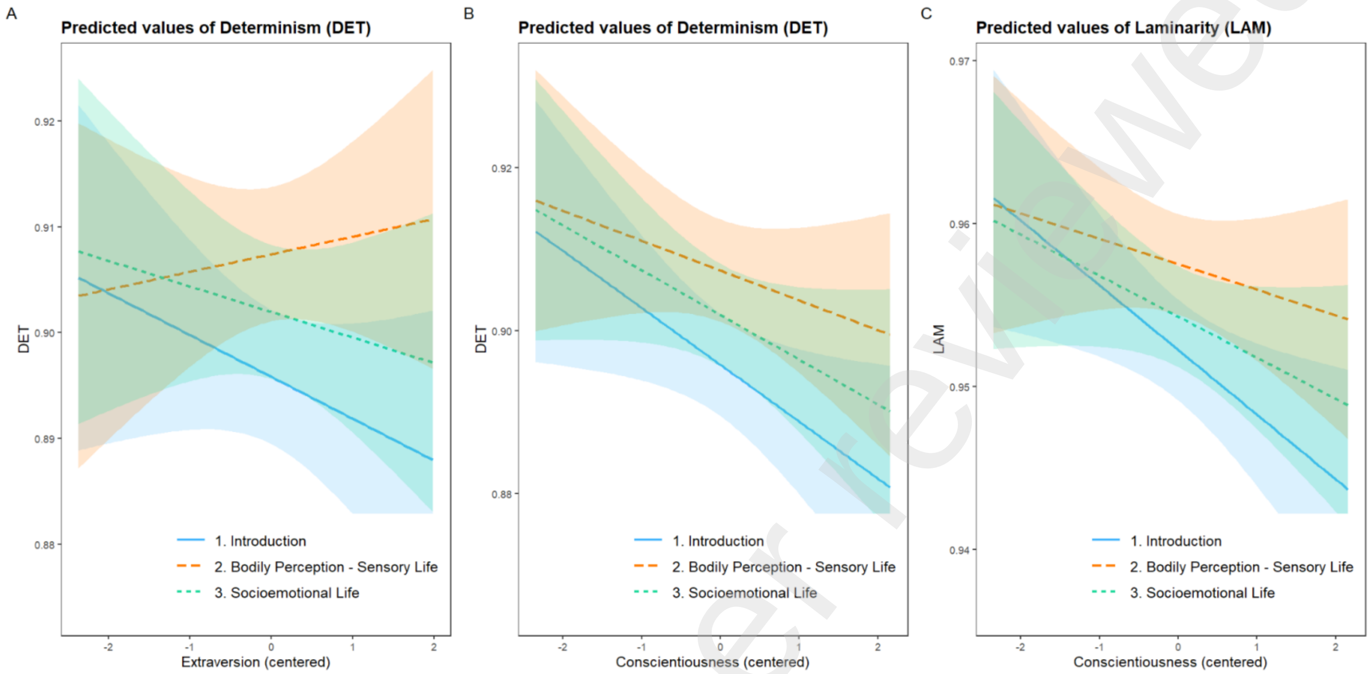
According to the full model of system Entropy ("complexity", see Table 7, model 6; $p < 0.001$, conditional $R^2 = .65$), the self-referencing topics of bodily perception/sensory life and socio-emotional life, predicted higher values of system entropy compared to the baseline topic in which participants introduced themselves. More neurotic participants who talked about their socio-emotional life (topic 3) showed lower system entropy ($p < 0.01$) which suggests less complexity in the dynamic self-organization during this particular topic, whereas lower neuroticism scores (thus emotional stability) predicted more complex motion patterns thus higher entropy (see Figure 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 8, model 6, $p < 0.001$), in support of topic effects (H1). Finally, in the model of Mean Line (dynamic stability, Table 9), the effect of neuroticism in interaction with socio-emotional life predicted lower values of Mean Line, indicating less dynamic stability ($p < 0.01$, conditional $R^2 = .54$), in line with the effects described in the short model and expectations (H2b). Overall, our results support personality differences in body motion dynamics between the self-referencing topics (across topics, H1b). Of the personality factors only conscientiousness predicted different body motion dynamics without interacting with any topic, but overall, personality differences surfaced most easily across the self-referencing topics.

3.4. Affect Valence

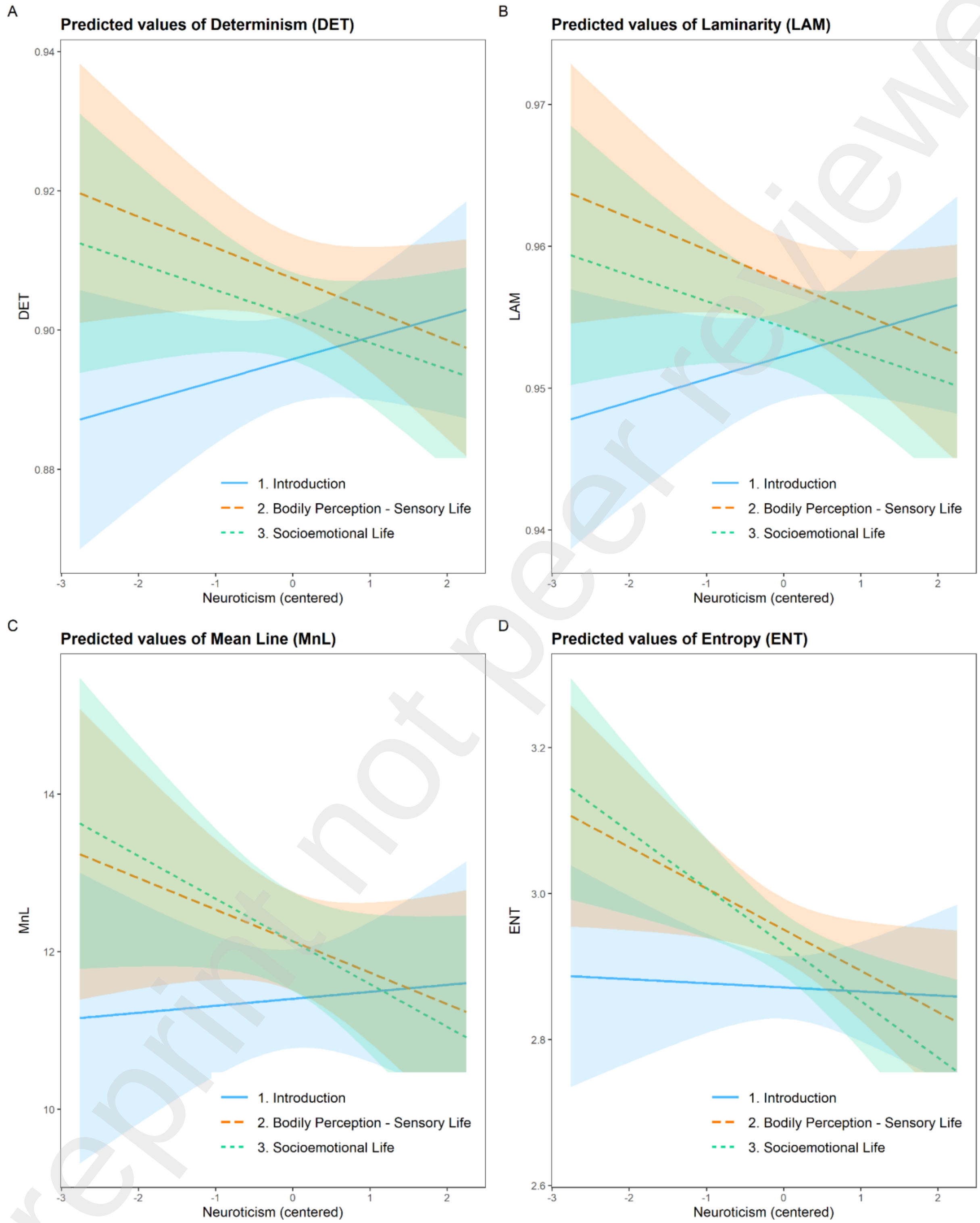
The descriptives of affect valence exhibited slightly higher mean values of positive affect post-task and slightly lower negative affect post-task (see Table 3). When testing the report of affect pre and post-task, the ANOVA tests revealed significant differences in negative affect ($F[1,101] = 7.50$, $p = 0.01$, $\eta^2 = 0.07$), but not in positive affect ($F[1,101] = 0.004$, $p = .94$, $\eta^2 = 0.00$) (two observations were removed due to missingness). To explore the effects of personality as predictors of positive and negative affect, general linear models suggested a significant effect of neuroticism predicting higher negative affect post-task ($p < 0.001$), in contrast to the effect of agreeableness, predicting lower negative affect post-task ($p < 0.001$) (Table 10). This model explains 11% of the variance of negative affect ($R^2 = .11$) and it has a medium effect size (Cohen's $d = .70$).

Figure 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. Figure 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. Figures 4B and 4C represent the effects of Conscientiousness on determinism and laminarity respectively which resulted in significant results independent of topic.

Figure 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.

4 Discussion

We studied how personality differences are expressed in body motion dynamics using enactive, embodied, and complex systems perspectives. Our study followed two aims: first, exploring the effects of "high-level" situational constraints on individual self-organization, as reflected in body motion dynamics (see introduction section). To accomplish this, we designed a simple study in which participants were invited to a laboratory where they introduced themselves, talked about their bodily perception/sensory life, and socio-emotional life, thus three self-referencing topics as high-level constraints. Second, we explored whether personality differences predicted how these high-level constraints influenced self-organizing dynamics derived from body motion. Our study yielded two general key observations. First, we established the relevance and explanatory power of high-level constraints (such as a self-referencing topic) to understand the dynamics of self-organized behavior as extracted from body motion dynamics in a standardized individual setting. Second, we showed how personality differences predicted and moderated the effect of the topic (or high-level constraint) on embodied (i.e. movement) dynamics. Both points and their implications are discussed in more detail below, followed by the limitations and conclusions of our study.

4.1 Effects of High-Level Constraints on Self-Organization

We observed significant differences elicited by the self-referencing topics in the self-organizing dynamics as expressed in whole-body motion (in line with H1), especially in terms of the degree of predictability (operationalized as Determinism), and complexity (operationalized as Entropy). The high-level constraints (self-referencing topics) predicted differences in all measures of dynamic self-organization, namely, more Determinism (predictability), Entropy (complexity), Laminar states, and Mean Line (stability). Apparently, once participants reflected on their bodily and sensory experiences and socio-emotional life, they started to show more organized, complex, stable, and fixated dynamics in the movement when contrasted with the self-introductory topic. These findings align with the self-pattern accounts of the self which holds that individuals are best understood when immersed in a meaningful environment that promotes flexibility and adaptation (Gallagher, 2013; Gallagher & Daly, 2018). In addition, we observed an overall reduction in negative affect after our participants completed the full session, suggesting that talking about self-referencing topics on their own, would have a "positive" effect, except for participants with high levels of neuroticism (low emotional stability).

In our study, the dynamical patterns in whole-body motion captured self-organizing processes that reflect an underlying current of sensations, feelings, thoughts, memories, emotions, and meaning (Gallagher & Daly, 2018; Di Paolo, 2021). The high-level constraints might have created situations that required individuals to adapt to changing environmental demands (self-organized criticality), thereby influencing their embodied dynamic self-organization through critical states (Goodwin, 2001; Plenz et al., 2021). Our results align with pioneering studies that illustrated 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).

4.2. Personality Differences and Their Modulation of Self-Organization

Of the personality traits, neuroticism was most predictive of the self-organizing dynamics of body motion (RQA) measures. More neurotic participants were more likely to show unpredictable, unstable, less complex, and more fluctuating/volatile motion dynamics (thus low emotional stability), 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 were most pronounced when participants talked about their socio-emotional life (topic 3). Arguably, these self-referencing topics promoted the emergence of critical states in the participants, and more neuroticism made such critical transitions more likely, in line with a heightened sensitivity to environmental demands and more rapid mood changes (e.g., Jeronimus, 2019). Contrarily, low neuroticism would predict more complex, predictable, 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 embodied dynamics using body motion information only (test-data), which were less visible in previous 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). Evidently, response mechanisms are trait and situation-specific (cf. Mischel and Shoda, 1995). Admittedly, we did not assess trait expression in our study, but the results indicate clear interactions between neuroticism and situational processes, expressed in the self-organizing dynamics exhibited in body motion.

As mentioned in the introduction, from an enactive view of personality traits, they function as stylistic differences in the way that individuals perceive and act in relation to their environments

(Hovhannisyan & Vervaeke, 2022; Todd & Gigerenzer, 2019; Satchell et al., 2021). Theorists using this approach introduced the dynamic meta-traits *Stability* and *Plasticity* in response to the meta-problem of uncertainty (or "*psychological entropy*", referred to as "the variation in the possibilities for action available to the cognitive agent" by De Young (2013) and 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 against perceived threats or uncertainty (i.e., psychological entropy, DeYoung, 2013). Phenomenologically, this could be observed in experiencing uncertainty as threatening and eliciting anxiety and defensive responses; however, this configuration makes individuals better adapted to threatening situations, in opposition to emotionally stable individuals who are less likely to experience uncertainty as threatening (Hovhannisyan & Vervaeke, 2022; Jeronimus, 2019). Highly neurotic (i.e. emotionally unstable) individuals could have experienced more anxiety when talking about their sensory and socioemotional experiences (topics 2 and 3), which would align with their body motion patterns and negative affect after the topic. Phenomenologically, this *instability* could have been *efficient* to them, as it represents a defensive/protective response. Conversely, low neurotic (thus emotionally stable) individuals would not feel anxious and were more prone to explore (more complex patterns of behavior), but also exhibited stability, predictability, and smoothness in their motion dynamics, which indicates well-adjusted self-organizing dynamics and systemic stability overall ("serenity").

For extraversion only the topic on sensory experiences (topic 2) was associated with more predictable patterns of self-organization, a topic effect that went opposite to effects observed in the introduction and socio-emotional topic (this last effect was not significant), which indicates a topic-specific effect. Without extraversion effects on Entropy (complexity), results only partially supported H1a. Arguably, focusing on one's body and perceptual experiences could elicit differentiated patterns of self-organization compared to an (alleged) self-introduction. Some authors describe a continuum in the affect sphere, evolving from bodily and sensorial affects to more elaborated and stable affective or emotional patterns (e.g., Barrett, 2017; Newen et al., 2015). This continuum was possibly captured in our experimental design, where the topic of bodily perception/sensory life may have invited participants to engage in self-awareness and concrete processes that were enacted through their body motion. The conceptualization of extraversion as a measure of social, gregarious, and outgoing behavior (McCrae & Costa, 2003) may explain the lack of extraversion effects via the individual nature of the topics, which were less extraversion-congruent (and more neuroticism-congruent). Moreover, extraversion has been described as a dynamical system optimizing for the reward value of uncertainty (dopaminergically regulated processes), which can phenomenologically promote exploration in response to perceived uncertainty (DeYoung 2013; Hovhannisyan & Vervaeke, 2022). Such processes could explain why highly extroverted individuals exhibit more deterministic (predictable) patterns in response to the topics of bodily perception/sensory life and no other effects (e.g., regarding Entropy). Possibly, the situation, which can be seen as concrete and oriented to oneself instead of social domains, was not optimal to see further effects.

More conscientious participants showed less Determinism and Laminarity in general (without interaction with the topic), which suggests less sensitivity to environmental or high-level constraints, and more behavioral stability regardless of the situation. In this sense, conscientiousness is a personality trait associated with self-discipline, organization, goal-directed behavior, and attention to detail (McCrae, 2004). Phenomenologically, conscientiousness represents variation in mechanisms that lead to following rules and prioritizing long-term goals, for example by displaying motivation and enabling mechanisms (*industriousness*) and reducing distractions (*orderliness*) (DeYoung, 2015; DeYoung & Weisberg, 2018). And it is thought to efficiently grip over ordering and planning depending on the goals to be achieved and their timescales (Rueter et al., 2018; Hovhannisyan & Vervaeke, 2022). We expected that conscientious participants showed *more* Determinism in their self-organizing dynamics (H2d), as a reflection of structure and controlled patterns (see introduction).

Our result aligns more with an understanding of conscientiousness as differences in detail orientation and adaptability (Ness et al., 2021). This can be linked to the characteristic of highly conscientious individuals to pay attention to subtle nuances in their movements –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, they may have adjusted their body motion based on the requirements of the topic while trying to display a high performance, leading to less deterministic (less regular/predictable), more variable (less laminar states), and possibly, efficient patterns. 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, among others. These mechanisms would lead to high performance, satisfaction, and reward; and importantly, all of them are predictive of high conscientiousness (Bates et al., 2023), which can help to understand our results as participants might have paid more attention when performing the task. However, we lack insight into the (potential) influence of interactions between the personality traits across situations on embodied dynamics (as highly conscientious and extroverted people may respond differently than conscientious-introverted people). In this sense, according to the literature, the conscientiousness component of industriousness is thought to enable possibilities for action and goal achieving, being negatively related to neuroticism and positively related to extraversion (higher reward sensitivity); while the component of orderliness is a selective constraint (reducing distraction) and is positively related to neuroticism and negatively related to extraversion –thus, rules would work as protective strategies against defensive responses to uncertainty (Rueter, 2018; Hovhannisyan & Vervaeke, 2022). These interactions indicate differentiated mechanisms toward situational demands, hence, they need to be considered in future research. It would be also relevant to explore interactions between the different system dynamic (RQA) measures, as different configurations may indicate different mechanisms and dynamics (for example, in interaction with Entropy, Laminarity, or Mean Line). We return to this last point below.

Differences in agreeableness and openness showed non-significant effects on differences in dynamic self-organization of body motion (H2c was not supported). Agreeable participants reported less negative affect after the task which may reflect the characteristic cooperation, compassion, warmth, politeness, transparency, and communion associated with high scores (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). These drivers can phenomenologically explain why highly agreeable individuals felt less negative affect after disclosing personal information –which was a self-referencing topic but also involved talking about their socio-emotional lives, for example, about their families and friends. Prior research has shown that communion is linked to taking others' perspectives when sharing information (Abele & Wojciszke, 2007). Nevertheless, the content of the participants' speech was not studied, and it would be relevant to incorporate in future research.

The absence of significant 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 was not optimal for capturing complexity in self-organizing dynamics captured in body motion by openness to experience.

Finally, it is important to emphasize that complex behavior refers to an intricate interplay between information (Entropy) and dis(equilibrium) (López-Ruiz et al., 1995). In the context of our study, to address the problem of uncertainty –referred by enactive theories of personality, we believe that individuals tend to an optimal balance between Entropy and equilibrium or stability (López-Ruiz et al., 1995). Entropy alone does not fully capture a system's complexity, as it is the emergent result of interactions among components when a new element emerges (complexity) due to uncertainty and the degree of dis-equilibrium within the system (López-Ruiz et al., 1995). Complexity then, becomes evident when the system reaches intermediate levels of disequilibrium (Mean Line) and uncertainty (Entropy), highlighting the dynamic interplay between these factors. It is crucial to recognize that complexity does not solely depend on Entropy but is also influenced by the interwoven relationship between uncertainty and disequilibrium. This is relevant to the extent that, it is relevant to study these dynamics and interactions (between measures) closely over time, as well as during specific tasks.

5 Conclusions, Limitations, and Future Directions

This paper exhibited the relevance of studying full agent/system dynamics considering embodied, enactive and complex systems perspectives and how they relate to personality traits. Our results extend the knowledge on enactive approaches to personality, emphasizing the role of situational constraints. It is relevant that future studies expand on different levels of analysis and phenomenological domains and first-person experiences. It would be also important to further study the mechanisms involved in the processes of dynamic self-organization.

As limitations, we recognize the modest size and nature of our sample, composed of undergraduate students and females in their majority. In addition, the laboratory task involved the presence of an experimenter, even though we followed a rigorous protocol. Besides, 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 are not considering the dynamism of these traits/states over time. Nevertheless, we acknowledge the functionality of these assessment tools, their psychometric properties, and the rigorous scientific work behind their development. On the other hand, RQA is a powerful tool for analyzing the patterns in time series, but we were not able to describe underlying mechanisms. Moreover, 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 place the results these measures reveal in the context of psychological constructs. In this sense, adopting multimodal and multimethod approaches is advised in future studies.

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7 Ethics statement and conflict of interest

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

8 ORCID

Nicol A. Arellano-Véliz: https://orcid. org/0000-0001-9974-7347

Ralf F. A. Cox: https://orcid.org/0000-0002-2992-5352

Bertus F. Jeronimus: https://orcid. org/0000-0003-2826-4537

Ramón D. Castillo: https://orcid.org/0000-0002-8505-5179

E. Saskia Kunnen https://orcid.org/0000-0002-7876-0750

9 CRediT author statement

Nicol Arellano-Véliz: Conceptualization, Methodology, Software, Investigation, Data Curation, Formal analysis, Writing-Original Draft. **Ralf Cox:** Conceptualization, Methodology, Software, Formal analysis, Writing-Review & Editing, Supervision. **Bertus Jeronimus:** Conceptualization, Methodology, Writing-Review & Editing, Supervision. **Ramon Castillo:** Conceptualization, Writing-Review & Editing, Supervision. **E. Saskia Kunnen:** Conceptualization, Writing-Review & Editing, Supervision.

10 Data availability

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

11 References

Abele, A. E., & Wojciszke, B. (2007). Agency and communion from the perspective of self versus others. *Journal of Personality and Social Psychology, 93*(5), 751–763. https://doi.org/10.1037/0022-3514.93.5.751

Abney, D. H., Paxton, A., Dale, R., and Kello, C. T. (2014). Complexity matching in dyadic conversation. *J. Exp. Psychol. Gen. 143*, 2304. https://doi.org/10.1037/xge0000021

Albright, L., Kenny, D. A., & Malloy, T. E. (1988). Consensus in personality judgments at zero acquaintance. *Journal of Personality and Social Psychology, 55*(3), 387–395. https://doi.org/10.1037/0022-3514.55.3.387

Ambady, N., & Rosenthal, R. (1992). Thin slices of expressive behavior as predictors of interpersonal consequences: A meta-analysis. Psychological Bulletin, 111(2), 256. https://doi.org/10.1037/0033-2909.111.2.256

Ambady, N., Bernieri, F. J., & Richeson, J. A. (2000). Towards histology of social behavior: Judgmental accuracy from thin slices of the behavioural stream. *Advances in Experimental Social Psychology, 32,* 201–271. http://dx.doi.org/10.1016/S0065-2601(00)80006-4.

Arellano-Véliz, N. A., Jeronimus, B. F., Kunnen, E. S., & Cox, R. F. A. (2023). The interacting partner as the immediate environment: Personality, interpersonal dynamics, and bodily synchronization. *Journal of Personality*. https://doi.org/10.1111/jopy.12828

Bak, T., and Wiesenfeld, K. (1987). Self-organized criticality: an explanation of the 1/f noise. *Phys. Rev. Lett. 59*, 381–384. doi: 10.1103/PhysRevLett.59.381

Bakan, D. (1966). *The duality of human existence: Isolation and communion in Western man*. Beacon Press.

Baron, R. M., & Boudreau, L. A. (1987). An ecological perspective on integrating personality and social psychology. *Journal of Personality and Social Psychology, 53,* 1222–1228. https://10.1037/0022-3514.53.6.1222

Barrett, L. F. (2017). *How emotions are made: The secret life of the brain*. Pan Macmillan.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Bates, T. C., Enkhbat, T., Gray, E., Lee, J., & Zakharin, M. (2023). How to get things done: Tight linkage of conscientiousness with twelve mechanisms of Goal Setting Theory. *Personality and Individual Differences, 214*(112331). https://doi.org/10.1016/j.paid.2023.112331

Baumert, A., Schmitt, M., Perugini, M., Johnson, W., Blum, G., Borkenau, P., Costantini, G., Denissen, J. J. A., Fleeson, W., Grafton, B., Jayawickreme, E., Kurzius, E., MacLeod, C., Miller, L. C., Read, S. J., Roberts, B., Robinson, M. D., Wood, D., and Wrzus, C. (2017). Integrating Personality Structure, Personality Process, and Personality Development. *European Journal of Personality, 31*(5), 503–528. https://doi.org/10.1002/per.2115

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, 57(1), 289–300.

Blake, R. & Shiffrar, M. (2007). Perception of Human Motion. *Annual Review of Psychology, 58*, 47-73. https://doi.org/10.1146/annurev.psych.57.102904.190152

Bleidorn, W., Schwaba, T., Zheng, A., Hopwood, C. J., Sosa, S. S., Roberts, B. W., & Briley, D. A. (2022). Personality stability and change: A meta-analysis of longitudinal studies. *Psychological Bulletin, 148*(7-8), 588-619. https://doi.org/10.1037/bul0000365

Bloch, C., Vogeley, K., Georgescu, A.L., & Falter-Wagner, C.M. (2019). INTRApersonal Synchrony as Constituent of INTERpersonal Synchrony and Its Relevance for Autism Spectrum Disorder. *Frontiers in Robotics and Artificial Intelligence, 6*(73). https://doi.org/10.3389/frobt.2019.00073

Box-Steffensmeier, J. M., Freeman, J. R., Hitt, M. P., & Pevehouse, J. C. (2014). *Time Series Analysis for the Social Sciences.* Cambridge University Press. https://doi.org/10.1017/cbo9781139025287

Bruineberg, J., Chemero, A. & Rietveld, E. (2019). General ecological information supports engagement with affordances for 'higher' cognition. *Synthese,* 196, 5231–5251. https://doi.org/10.1007/s11229-018-1716-9

Buss, D.M. (1991). Evolutionary Personality Psychology. *Annual Review of Psychology, 42*, 459-491. https://doi.org/10.1146/annurev.ps.42.020191.002331

Buss, D. M. (2019). *Evolutionary psychology: The New Science of the Mind,* (6th ed.). Routledge. https://doi.org/10.4324/9780429061417

Busa, M.A., & an Emmerik, R.E.A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *Journal of Sport and Health Science, 5*(1), 44-51. https://doi.org/10.1016/j.jshs.2016.01.018

Carney, D. R., Colvin, C. R., & Hall, J. A. (2007). A thin slice perspective on the accuracy of first impressions. *Journal of Research in Personality, 41*(5), 1054-1072. https://doi.org/10.1016/j.jrp.2007.01.004

Chemero, A. (2003). An Outline of a Theory of Affordances. *Ecological Psychology, 15*(2), 181–195. https://doi.org/10.1207/S15326969ECO1502_5

Chemero, A. (2013). *Radical embodied cognitive science*. Cambridge: MIT Press

Carruthers, P., Laurence, S., & Stich, S. P. (Eds.). (2005). The innate mind (Vol. 1-3). Oxford University Press.

Coco, M. I., Badino, L., Cipresso, P., Chirico, A., Ferrari, E., Riva, G., Gaggioli, A., & D'ausilio, A. (2017). Multilevel behavioral synchronization in a joint tower-building task. *IEEE Transactions on Cognitive and Developmental Systems, 9*(3), 223–233. https://doi.org/10.1109/TCDS.2016.2545739

Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Curtin, P., Curtin, A., Austin, C., Gennings, C., Tammimies, K., Bolte, S., & Arora, M. (2017). Recurrence quantification analysis to characterize cyclical components of environmental elemental exposures during fetal and postnatal development. *PLoS ONE, 12*(11), e0187049. https://doi.org/10.1371/journal.pone.0187049

Davis, T.J., Brooks, Thomas, R. & Dixon, J.A. (2016). Multi-scale interactions in interpersonal coordination. *Journal of Sport and Health Science, 5,* 25-34. http://dx.doi.org/10.1016/j.jshs.2016.01.015

Dawkins, R. (2016). *The extended phenotype: The long reach of the gene*. Oxford University Press.

Denissen, J. J. A., Butalid, L., Penke, L., & van Aken, M. A. G. (2008). The effects of weather on daily mood: A multilevel approach. *Emotion, 8*(5), 662–667. https://doi.org/10.1037/a0013497

De Jonge-Hoekstra, L., Van Der Steen, S., & Cox, R. F. A. (2020). Movers and shakers of cognition: Hand movements, speech, task properties, and variability. *Acta Psychologica, 211,* 103187. https://doi.org/10.1016/j.actpsy.2020.103187

DeYoung, C. G. (2006). Higher-order factors of the Big Five in a multi-informant sample. *Journal of Personality and Social Psychology, 91*, 1138–1151. https://doi.org/10.1037/0022-3514.91.6.1138

DeYoung, C. G. (2013). The neuromodulator of exploration: A unifying theory of the role of dopamine in personality. *Frontiers in Human Neuroscience, 7*. https://doi.org/10.3389/fnhum.2013.00762

DeYoung, C. G. (2015). Cybernetic big five theory. *Journal of Research in Personality, 56*, 33–58. http://dx.doi.org/10.1016/j.jrp.2014.07.004.

DeYoung, C. G., & Weisberg, Y. J. (2018). *Cybernetic Approaches to Personality and Social Behavior.* https://doi.org/10.1093/oxfordhb/9780190224837.013.25

Dimitriev, D., Saperova, E.V., Dimitriev, A. & Karpenko, Y. (2020) Recurrence Quantification Analysis of Heart Rate During Mental Arithmetic Stress in Young Females. *Frontierts in Physiology, 11*(40). https://doi.org/10.3389/fphys.2020.00040

Di Paolo, E., & Thompson, E. (2014). The enactive approach. In L. Shapiro (Ed.), *The Routledge handbook of embodied cognition,* (pp. 68–78). Routledge/Taylor & Francis Group.

Di Paolo, E. A., Buhrmann, T., & Barandiaran, X. E. (2017). *Sensorimotor Life: An Enactive Proposal*. Oxford University Press.

Di Paolo, E. (2021). Enactive becoming. *Phenomenology and the Cognitive Sciences, 20*, 783-809. https://doi.org/10.1007/s11097-019-09654-1

Fajkowska, M. (2015). The Complex-System Approach to Personality: Main theoretical assumptions. *Journal of Research in Personality, 56*, 15-32. https://doi.org/10.1016/j.jrp.2014.09.003

Fetterman, A., Robinson, S., Ode, S. & Gordon, K. (2010). Neuroticism as a risk factor for behavioral dysregulation: A mindfulness-meditation perspective. *Journal of Social and Clinical Psychology, 29*(3), 301-321.

Fleeson, W., & Jayawickreme, E. (2021). Whole traits: Revealing the social-cognitive mechanisms constituting personality's central variable. In B. Gawronski (Ed.), *Advances in experimental social psychology* (pp. 69–128). Elsevier Academic Press. https://doi.org/10.1016/bs.aesp.2020.11.002

Fuchs, T. (2017). *Ecology of the Brain: The phenomenology and biology of the embodied mind.* https://doi.org/10.1093/med/9780199646883.001.0001

Fuchs, T. (2020). The Circularity of the Embodied Mind. *Frontiers in Psychology, 11*(1707). https://doi.org/10.3389/fpsyg.2020.01707

Galbusera, L., Finn, M. T. M., Tschacher, W., & Kyselo, M. (2019). Interpersonal synchrony feels good but impedes self-regulation of affect. *Nature Scientific Reports, 9*, 14691. https://doi.org/10.1038/s41598-019-50960-0

Gallagher, S. (2012). Multiple aspects of agency. *New Ideas Psychology, 30,* 15–31. https://doi.org/10.1016/j.newideapsych.2010.03.003

Gallagher, S. (2013). A Pattern Theory of Self. *Frontiers in Human Neuroscience, 7*, 55769. https://doi.org/10.3389/fnhum.2013.00443

Gallagher, S., & Daly, A. (2018). Dynamical Relations in the Self-Pattern. *Frontiers in Psychology, 9,* 359003. https://doi.org/10.3389/fpsyg.2018.00664

García, C. (2022). nonlinearTseries: Nonlinear Time Series Analysis. R package version 0.2.12. https://CRAN.R-project.org/package=nonlinearTseries

Gibson, J. J. (1979). *The ecological approach to visual perception*. Psychology Press.

Gocłowska, M. A., Ritter, S. M., Elliot, A. J., & Baas, M. (2019). Novelty seeking is linked to openness and extraversion, and can lead to greater creative performance. *Journal of Personality, 87*(2), 252-266. https://doi.org/10.1111/jopy.12387

Goodwin, B. (2001). Evolution: Self-organization Theory. *International Encyclopedia of the Social & Behavioral Sciences,* 5003-5007. https://doi.org/10.1016/B0-08-043076-7/03081-3

Hovhannisyan, G., Vervaeke, J. (2022). Enactivist Big Five Theory. *Phenomenology and Cognitive Sciences, 21*, 341–375. https://doi.org/10.1007/s11097-021-09768-5

Hox, J., Moerbeek, M., & van de Schoot, R. (2017). *Multilevel Analysis: Techniques and Applications,* (3rd ed.). Routledge. https://doi.org/10.4324/9781315650982

Hu, Y., Cheng, X., Pan, Y., & Hu, H. (2022). The intrapersonal and interpersonal consequences of interpersonal synchrony. *Acta Psychologica, 224,* 103513. https://doi.org/10.1016/j.actpsy.2022.103513

Jeronimus, B. F. (2019). Dynamic System Perspectives on Anxiety and Depression. In S. Kunnen, N. de Ruiter, B. Jeronimus, & M. van der Gaag (Eds.), *Psychosocial Development in Adolescence: Insights from the Dynamic Systems Approach* (1 ed., pp. 100-126). (Studies in Adolescent Development). Routledge. https://doi.org/10.4324/9781315165844-7

Jiang, S., Paxton, A., Ramírez-Esparza, N., & García-Sierra, A. (2023). Toward a dynamic approach of person perception at zero acquaintance: Applying recurrence quantification analysis to thin slices. *Acta Psychologica, 234*, 103866. https://doi.org/10.1016/j.actpsy.2023.103866

Johnson, J. A. (2014). Measuring thirty facets of the five-factor model with a 120-item public domain inventory: Development of the IPIP-NEO-120. *Journal of Research in Personality, 51,* 78–89. https://doi.org/10.1016/j.jrp.2014.05.003

Johnson, M. (2015). Embodied understanding. *Frontiers in Psychology, 6*(875), 1-8. https://doi.org/10.3389/fpsyg.2015.00875

Kelso, J., & Schöner, G. (1988). Self-organization of coordinative movement patterns. *Human Movement Science, 7*(1), 27-46. https://doi.org/10.1016/0167-9457(88)90003-6

Kenny, D.A, Horner, C., Kashy, D.A. & Chu, L.C. (1992). Consensus at zero acquaintance: replication, behavioral cues, and stability. *Journal of Personality and Social Psychology, 62*(1), 88-97. https://doi.org/10.1037//0022-3514.62.1.88. PMID: 1538316.

Kleinbub, J. R., & Ramseyer, F. (2021). rMEA: An R package to assess nonverbal synchronization in motion energy analysis time-series. *Psychotherapy Research, 31*(6), 817– 830. https://doi.org/10.1080/10503 307.2020.1844334

Konvalinka, I., Xygalatas, D., Bulbulia, J., Schjødt, U., Jegindø, E.-M., Wallot, S., Van Irden, G., & Roepstoff, A. (2011). Synchronized arousal between performers and related spectators in a firewalking ritual. *Proceedings of the National Academy of Sciences of the United States of America, 108*(20), 8514–5819. https://doi. org/10.1073/pnas.1016955108

Koppensteiner, M. (2011). Perceiving personality in simple motion cues. *Journal of Research in Personality, 45*(4), 358-363. https://doi.org/10.1016/j.jrp.2011.04.003

Koppensteiner, M. (2013). Motion cues that make an impression: Predicting perceived personality by minimal motion information. *Journal of Experimental Social Psychology, 49*(6), 1137– 1143. https://doi.org/10.1016/j.jesp.2013.08.002

Koppensteiner, M., Stephan, P., & Jäschke, J. P. M. (2016). Moving speeches: Dominance, trustworthiness and competence in body motion. *Personality and Individual Differences, 94*, 101-106. https://doi.org/10.1016/j.paid.2016.01.013

Kunnen, S. (Ed.). (2012). *A dynamic systems approach to adolescent development.* Psychology Press.

Larsen, R. J., Buss, D. M., Wismeijer, A., Song, J., van den Berg, S., & Jeronimus, B. F. (2020). *Personality Psychology: Domains Of Knowledge About Human Nature.* (3 ed.) McGraw-Hill.

Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American Psychologist, 57*(9), 705–717. https://doi.org/10.1037//0003-066X.57.9.705

Locke, E. A., & Latham, G. P. (2019). The development of goal setting theory: A half century retrospective. *Motivation Science, 5*(2), 93–105. https://doi.org/10.1037/ mot0000127

López-Ruiz, R., Mancini, H.L. & Calbet, X. (1995). A statistical measure of complexity. *Physics Letters A, 209*(5-6), 321-326. https://doi.org/10.1016/0375-9601(95)00867-5

Luck, G., Saarikallio, S., Burger, B., Thompson, M., & Toiviainen, P. (2010). Effects of the Big Five and musical genre on music-induced movement. *Journal of Research in Personality, 44*(6), 714-720. https://doi.org/10.1016/j.jrp.2010.10.001

Mader, N., Arslan, R. C., Schmukle, S. C., & Rohrer, J. M. (2023). Emotional (in) stability: Neuroticism is associated with increased variability in negative emotion after all. *Proceedings of the National Academy of Sciences, 120*(23). https://doi.org/10.1073/pnas.2212154120

Manor, B., Costa, M.D., Hu, K., Newton, E., Starobinets, O., Kang, H.G., Peng, C.K., Novak, V. & Lipsitz, L.A. (2010). Physiological complexity and system adaptability: Evidence from postural control dynamics of older adults. *Journal of Applied Physiology, 103,* 1786–1791. https://doi.org/10.1152%2Fjapplphysiol.00390.2010

Marwan, N., Wessel, N., Meyerfeldt, U., Schirdewan, A., & Kurths, J. (2002). Recurrence-plot-based measures of complexity and their application to heart rate variability data. *Physical Review E, 66,* 026702.1-026702.8

Marwan, N., Romano, M. C., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Physics Reports, 438*(5–6), 237–329. https://doi.org/10.1016/j.physrep.2006.11.001ogan

Marwan, N., Webber, C.L. (2015). Mathematical and Computational Foundations of Recurrence Quantifications. In: Webber, Jr., C., Marwan, N. (eds) *Recurrence Quantification Analysis. Understanding Complex Systems*. Springer, Cham. https://doi.org/10.1007/978-3-319-07155-8_1

McCrae, R. R., & Costa, P. T. (2003). *Personality in adulthood: A five-factor theory perspective* (2nd

ed.). The Guilford Press.

McCrae, R.R. (2004). *"Conscientiousness" Encyclopedia of Applied Psychology.* Academic Press.

Mischel, W., & Shoda, Y. (1995). A cognitive-affective system theory of personality: reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. *Psychological review, 102*(2), 246. https://doi.org/10.1037/0033-295x.102.2.246

Michaels, J. L., Vallacher, R. R., & Nowak, A. (2021). Finding order in the flow of personality: Dynamical systems techniques for measuring personality coherence and change. In J. F. Rauthmann (Ed.), *The* *handbook of personality dynamics and processes* (pp. 985–1011). Elsevier Academic Press. https://doi.org/10.1016/B978-0-12-813995-0.00038-8

Newen, A., Welpinghus, A., & Juckel, G. (2015). Emotion Recognition as Pattern Recognition: The Relevance of Perception. *Mind & Language, 30*(2), 187-208. https://doi.org/10.1111/mila.12077

Ness, A. M., Foley, K. O., & Heggestad, E. (2021). Intra-individual variability in personality: A methodological review. *Measuring and Modeling Persons and Situations,* 313-353. https://doi.org/10.1016/B978-0-12-819200-9.00007-7

Nowak, A., Vallacher, R., Praszkier, R., Rychwalska, A., & Zochowski, M. (2020). *In sync: The emergence of function in minds, groups and societies.* Springer Nature Switzerland. https://doi.org/10.1007/978-3-030-38987-1

Oshio, A., Taku, K., Hirano, M., & Saeed, G. (2018). Resilience and Big Five personality traits: A meta-analysis. *Personality and Individual Differences, 127*, 54-60. https://doi.org/10.1016/j.paid.2018.01.048

Paxton, A., Dale, R. (2013). Frame-differencing methods for measuring bodily synchrony in conversation. *Behav Res, 45*, 329–343. https://doi.org/10.3758/s13428-012-0249-2

Paxton, A., & Dale, R. (2017). Interpersonal Movement Synchrony Responds to High- and Low-Level Conversational Constraints. *Frontiers in Psychology*, *8*, 235014. https://doi.org/10.3389/fpsyg.2017.01135

Plenz, D., Ribeiro, T. L., Miller, S. R., Kells, P. A., Vakili, A., & Capek, E. L. (2021). Self-Organized Criticality in the Brain. *Frontiers in Physics, 9.* https://doi.org/10.3389/fphy.2021.639389

Pross, A. (2016). *What is life?: How chemistry becomes biology.* Oxford University Press.

Rauthmann, J. F. (2021). Capturing interactions, correlations, fits, and transactions: A Person-Environment Relations Model. In J.F. Rauthmann, *The Handbook of Personality Dynamics and Processes* (pp. 427–522). https://doi.org/10.1016/b978-0-12-813995-0.00018-2

Revelle, W. (2023). *Procedures for Psychological, Psychometric, and Personality Research*. R package version 2.2.3. https://CRAN.R-project.org/package=psych

R Core Team (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Ramseyer, F. T. (2018). MEA: Motion energy analysis [computer software]. http://www.psync.ch

Ramseyer, F. T. (2020). Motion energy analysis (MEA): A primer on the assessment of motion from video. *Journal of Counseling Psychology, 67*(4), 536– 549. https://doi.org/10.1037/cou0000407

Richard, F. D., Bond, C. F., & Stokes-Zoota, J. J. (2003). One hundred years of social psychology quantitatively described. *Review of General Psychology, 7*(4), 331–363. https://doi.org/10.1037/1089-2680.7.4.331

Richardson, M. & Chemero (2014). Complex Dynamical Systems and Embodiment. In L. Shapiro (Ed.). *The Routledge Handbook of Embodied Cognition.* Routledge Taylor & Francis Group.

Riley, M. A., & Van Orden, G. C. (2005). Tutorials in contemporary nonlinear methods for the behavioral sciences.

Rietveld, E. & Kiverstein, J. (2014). A Rich Landscape of Affordances. *Ecological Psychology, 26*(4), 325-352. https://doi.org/10.1080/10407413.2014.958035

Robinson, M. D., Ode, S., Moeller, S. K., & Goetz, P. W. (2007). Neuroticism and affective priming: Evidence for a neuroticism-linked negative schema. *Personality and Individual Differences, 42*(7), 1221-1231. https://doi.org/10.1016/j.paid.2006.09.027

Rueter, A. R., Abram, S. V., MacDonald, A. W., III., Rustichini, A., & DeYoung, C. G. (2018). The goal priority network as a neural substrate of conscientiousness. *Human Brain Mapping, 39*(9), 3574–3585. https://doi.org/10.1002/hbm.24195

Sassenberg, T. A., Burton, P. C., Mwilambwe-Tshilobo, L., Jung, R. E., Rustichini, A., Spreng, R. N., & DeYoung, C. G. (2023). Conscientiousness associated with efficiency of the salience/ventral attention network: Replication in three samples using individualized parcellation. *NeuroImage, 272*, 120081. https://doi.org/10.1016/j.neuroimage.2023.120081

Satchell, L. P., Kaaronen, R. O., & Latzman, R. D. (2021). An ecological approach to personality: Psychological traits as drivers and consequences of active perception. S*ocial and Personality Psychology Compass, 15*(5), 1-14. https://doi.org/10.1111/spc3.12595

Schloesser, D.S., Kello, C.T. & Marmelat, V. (2019). Complexity matching and coordination in individual and dyadic performance. *Human Movement Science, 66,* 258-272. https://doi.org/10.1016/j.humov.2019.04.010

Schönbrodt, F. D., & Perugini, M. (2013). At what sample size do correlations stabilize? Journal of *Research in Personality, 47*(5), 609–612. https://doi.org/10.1016/j.jrp.2013.05.009

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal, 27*(3), 379-423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Sosnowska, J., Kuppens, P., De Fruyt, F., & Hofmans, J. (2019). A dynamic systems approach to personality: The Personality Dynamics (PersDyn) model. *Personality and Individual Differences, 144*, 11-18. https://doi.org/10.1016/j.paid.2019.02.013

Sviridova, N. & Ikeguchi, T. (2022). Detecting Determinism in Noisy Time Series with Variable Minimal Diagonal Line Length in Recurrence Quantification Analysis. *International Symposium on Nonlinear Theory and Its Applications*. December 12-15, 2022.

Tett, R. P., & Guterman, H. A. (2000). Situation trait relevance, trait expression, and cross-situational consistency: Testing a principle of trait activation. *Journal of Research in Personality, 34*(4), 397–423. https://doi.org/10.1006/jrpe.2000.2292

Thompson, E. (2007). Development and validation of an internationally reliable short-form of the positive and negative affect schedule (PANAS). *Journal of Cross-Cultural Psychology, 38*(2), 227–242. https://doi.org/10.1177/0022022106297301

Thompson, E. (2010). *Mind in Life Biology, Phenomenology, and the Sciences of Mind.* Harvard University Press.

Thiel., M., Romano, M.C., Kurths, J., Meucci, R., Allaria, E., Arecchi., T. (2002). Influence of observational noise on the recurrence quantification analysis. *Physica, 171*, 138-152.

Tooby, J., & Cosmides, L. (1992). The psychological foundations of culture. *The adapted mind: Evolutionary psychology and the generation of culture, 19,* 19-136.

Todd, P. M., & Gigerenzer, G. (2020). The ecological rationality of situations: Behavior = f(adaptive toolbox, environment). In J. F. Rauthmann, R. A. Sherman, & D. C. Funder (Eds.), *The Oxford Handbook of Psychological Situations* (pp. 143-158). New York: Oxford University Press. doi:10.1093/oxfordhb/9780190263348.013.29.

Tommasini, F.C., Evin, D.A., Bermejo, F., Hug, M., Barrios, V. & Pampaluna, A. (2022). Recurrence analysis of sensorimotor trajectories in a minimalist perceptual task using sonification. *Cognitive Processing, 23*, 285–298. https://doi.org/10.1007/s10339-021-01068-9

Tschacher, W., Ramseyer, F., & Koole, S. L. (2018). Sharing the Now in the Social Present: Duration of Nonverbal Synchrony Is Linked With Personality. Journal of Personality, 86(2), 129-138. https://doi.org/10.1111/jopy.12298

Vallacher, R. R., Read, S. J., & Nowak, A. (2002). The dynamical perspective in personality and social psychology. *Personality and Social Psychology Review, 6*(4), 264–273. https://doi.org/10.1207/S15327957PSPR0604_01

Vallacher, R. R., Michaels, J. L., Wiese, S., Strawinska, U., & Nowak, A. (2013). Mental dynamism and its constraints. Finding patterns in the stream of consciousness. In D. Cervone, M. Fajkowska, M. W. Eysenck, & T. Maruszewski (Eds.), *Personality dynamics: Meaning construction, the social world, and the embodied mind* (pp. 159–181). Clinton Corners, NY: Eliot Werner Publications.

van den Hoorn, W., Hodges, P. W., van Dieën, J. H., & Kerr, G. K. (2020). Reliability of recurrence quantification analysis of postural sway data. A comparison of two methods to determine recurrence thresholds. *Journal of Biomechanics, 107,* 109793. https://doi.org/10.1016/j.jbiomech.2020.109793

Varela, F. J., Tompson, E. & Rosch, E. (2017). *The Embodied Mind: Cognitive Science and Human Experience, Revised edition*. MIT Press. (Original work published 1991).

Von Neumann, J., Kent, R., Bellinson, H., & Hart, B. (1941). The mean square successive difference. *The Annals of Mathematical Statistics*, 153-162.

Wallot, S. & Leonardi G (2018). Analyzing Multivariate Dynamics Using Cross-Recurrence Quantification Analysis (CRQA), Diagonal-Cross-Recurrence Profiles (DCRP), and Multidimensional Recurrence Quantification Analysis (MdRQA) – A Tutorial in R. *Frontiers in Psychology, 9*(2232). https://10.3389/fpsyg.2018.02232

Webber, C. & Zbilut, J. (2005). Recurrence Quantification Analysis of Nonlinear Dynamical Systems. In M.A. Riley & G.C. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences*.

Wilt, J. A., & Revelle, W. (2017). The Big Five, everyday contexts and activities, and affective experience. *Personality and Individual Differences*, *136*, 140–147. https://doi.org/10.1016/j.paid.2017.12.032

Wijnants, M. L., Hasselman, F., Cox, R. F. A., Bosman, A. M. T., & Van Orden, G. (2012). An interaction-dominant perspective on reading fluency and dyslexia. *Annals of Dyslexia, 62*, 100–229. https://doi.org/10.1007/s11881-012-0067-3

Wrzus, C., & Mehl, M. R. (2015). Lab And/Or Field? Measuring Personality Processes and Their Social Consequences. *European Journal of Personality, 29*(2). https://doi.org/10.1002/per.1986

Xin, Y., Wu, J., Yao, Z., Guan, Q., Aleman, A., & Luo, Y. (2017). The relationship between personality and the response to acute psychological stress. *Nature Scientific Reports, 7*. https://doi.org/10.1038/s41598-017-17053-2

Xu, T.L., de Barbaro, K, Abney, D.H. & Cox, R.F.A. (2020) Finding Structure in Time: Visualizing and Analyzing Behavioral Time Series. Frontiers in Psychology, 11(1457). https://doi.org/10.3389/fpsyg.2020.01457

Table 1

Variables Operationalization, Definition, and Statistical Analyses[*]

Dynamic Self-Organization: Intrapersonal dynamics of body movement based on Motion Energy Analysis		
Strategy Step 1: Nonlinear time-series analysis measuring the temporal structure and self-organization of body motion. *Technique:* Recurrence Quantification Analysis (RQA).		
Variable	**Definition**	**Interpretation**
Determinism (DET)	Proportion of recurrences ≥ 4 along *diagonal* lines in the recurrence plot, where line length i.e. periods of recurrences varies (as detailed in MnL).[1-3]	Estimates predictability of the time series in terms of signal regularity.[2,4] Higher DET values (0-1) tend to indicate more consistent and predictable 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]	Estimates the *complexity* of the system's deterministic structures and low(er) ENT values suggest a greater likelihood of repeating, regular, and more rigid paths. Higher ENT values suggest greater heterogeneity in the duration of recurrent paths or trajectories.[5] Higher scores can indicate both higher irregularity and more complexity/flexibility in the system trajectories.[2,6] Importantly, 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*.[†] Laminar structures are episodes in which the system is "captured" in a particular state known as an attractor state. 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 predictable system behavior (attractor) while low(er) LAM values indicate more variable system dynamics.[4,5,10]

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, and particularly, the average time by which two segments of a trajectory are close to each other.[3,6]	Estimates system stability as short MnL indicates unpredictable (irregular) dynamics and longer MnL indicate stable and predictable dynamics.[3]
Step 2: Statistical analysis		
a. Descriptive statistics for full-body motion dynamics (e.g., mean, SD, median, range). b. Hierarchical models predicting dynamic self-organization of body motion from personality traits and high-level constraints/topics (Level 1: RQA measures by self-referencing topics; Level 2: Individuals) c. Post-task exploratory measures: affect-state in relation to RQA measures		
Dynamic self-organization of motor behavior in the RQA is thought to reflect a sensorimotor system that adapts to contexts and shows more Determinism (predictability), Entropy (i.e., complexity, which would indicate flexibility and adaptability), more laminar states (which can also indicate periods of inflexibility or rigidity but their absence suggests volatile dynamics); and more stability in terms of higher Mean Line values.		

[*] Table adapted from Arellano-Véliz ea. (2023). [†] Intermittency refers to an irregular alternation of phases of apparently periodic (organized) and chaotic (disorganized) dynamics. [1] Curtin ea. (2017). [2] McCamley ea. (2017). [3] Marwan ea. (2007). [4] Konvalinka ea. (2011). [5] Tomassini ea. (2022). [6] Wallot & Leonardi (2018). [7] López-Ruiz ea. (1995). [8] Marwan ea. (2002). [9] Webber & Zbilut, 2005. [10] Dimitriev ea. (2020).
For equations of each RQA measure, see Tomassini ea. (2022).

Table 2.
Descriptive statistics linear and RQA measures of body motion

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

Table 4.

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 $^{*}p< .05$ and $^{**}p < .01$.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 5.
*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 (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)
Intercept	.90 (.003)***	2.87 (.023)***	0.95 (.002)***	11.40 (.321)***
Topic 2 (T.2)	.001 (.002)***	.08 (.021)***	.005 (.001)***	.73 (.318)*
Topic 3 (T.3)	.001 (.006)*	.06 (.021)**	.002 (.001)	.73 (.318)*
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
Cohen's *d* (Marg.R^2/Cond.R^2)	.28 / 2.56 (small/large)	.28 / 2.35 (small/large)	.28 / 2.61 (small/large)	.20 / 2.08 (small/large)

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

Table 6.
*Mixed-Effects Models predicting Determinism. Ni = 105; Nt = 315 observations (105i * 3 topics)*

	M1. E	M2. N	M3. A	M4. C	M5. O	M6. Full model
Predictors	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)
Intercept	.90(.02)***	.90(.003)***	.90(.003)***	.90(.003)***	.90(.003)***	.91 (.002)***
Extraversion	-.004(.003)					-.004(.004)
Neuroticism		.003(.003)				-.001(.004)
Agreeableness			-.001(.003)			.006(.003)
Conscient.				-.007(.003)*		-.007(.003)
Openness					.003(.003)	.005(.003)
Topic 2 (T.2)	.001(.003)***	.012(.003)***	.001(.003)***	.012(.003)***	.012(.003)***	.022(.003)***
Topic 3 (T.3)	.006(.003)*	.006(.003)*	.006(.003)*	.006(.003)*	.006(.003)*	.006(.003)
Extraversion*T.2	.006(.003)*					.001(.003)
Extraversion*T.3	.002(.003)					-.004(.003)
Neuroticism*T.2		-.008(.003)**				-.007(.003)
Neuroticism*T.3		-.007(.003)*				-.009(.003)*
Agreeableness*T.2			-.000(.003)			-.004(.003)
Agreeableness*T.3			.001(.003)			-.001(.003)
Conscient.*T.2				.003(.003)		.002(.003)
Conscient.*T.3				.001(.003)		-.000(.003)
Openness*T.2					.002(.003)	.003(.003)
Openness*T.3					.001(.002)	.003(.003)
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
Cohen's *d* (Marg.R^2/Cond.R^2)	.35 / 2.67 (small/large)	.35 / 2.67 (small/large)	.28 / 2.55 (small/large)	.46 / 2.56 (small/large)	.35 / 2.56 (small/large)	0.70 / 2.67 (medium/large)

*Note: * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p*-values were corrected in the full model by Benjamini-Hochberg (Benjamini & Hochberg, 1995) FDR procedure. T2 = Topic 2, bodily perception/sensory life; T3 = Task 3, socio-emotional life. E=Extraversion, N=Neuroticism, A=Agreeableness, C/Conscient. = Conscientiousness, O=Openness. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled.

Table 7.
*Mixed-Effects Models predicting Entropy. Ni = 105; Nt = 315 observations (105i * 3 topics)*

	M1. E	M2. N	M3. A	M4. C	M5. O	M6. Full model
Predictors	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)
Intercept	2.87(.023)***	2.87(.023)***	2.87(.023)***	2.87(.023)***	2.87(.023)***	2.87(.021)***
Extraversion	-.017(.023)					-.020(.027)
Neuroticism		.001(.001)				-.006(.027)
Agreeableness			.015(.022)			.025(.025)
Conscientiousness				-.034(.023)		-.004(.023)
Openness					.012(.023)	.015(.025)
Topic 2 (T.2)	.079(.021)***	.079(.021)***	.079(.021)***	.079(.021)***	.079(.021)***	.079(.020)**
Topic 3 (T.3)	.059(.021)**	.059(.021)**	.059(.021)**	.059(.021)**	.059(.021)**	.059(.020)*
Extraversion* T.2	.026(.021)					-.001(.020)
Extraversion * T.3	-.013(.021)					-.051(.025)
Neuroticism * T.2		-.003(.001)				-.051(.003)
Neuroticism * T.3		-.002(.001)				-.072(.025)*
Agreeableness* T.2			-.020(.021)			-.047(.023)
Agreeableness* T.3			-.018(.021)			-.034(.027)
Conscient.* T.2				.058(.021)		.012(.023)
Conscient.* T.3				-.003(.021)		-.003(.022)
Openness * T.2					.019(.021)	.036(.023)
Openness* T.3					.008(.021)	.039(.023)
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
Cohen's *d* (Marg.R^2/Cond.R^2)	.28 / 2.40 (small/large)	.35 / 2.40 (small/large)	.28 / 2.35 (small/large)	.41 / 2.35 (small/large)	.35 / 2.35 (small/large)	.63 / 2.50 (medium/large)

*Note: * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p*-values were corrected in the full model by Benjamini-Hochberg (Benjamini & Hochberg, 1995) FDR procedure. T.2 = Topic 2, bodily perception/sensory life; T.3 = Topic 3, socio-emotional life. E=Extraversion, N=Neuroticism, A=Agreeableness, C/Conscient. = Conscientiousness, O=Openness. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled.

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

	M1. E	M2. N	M3. A	M4. C	M5. O	M6. Full model
Predictors	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)
Intercept	.95(.002)***	.95(.002)***	.95(.002)	.95(.002)	.95(.001)***	.95(.002)***
Extraversion	-.002(.002)					-.190(.002)
Neuroticism		.002(.002)				-.000(.002)
Agreeableness			-.001(.002)			.000(.002)
Conscientiousness				-.004(.002)*		-.004(.002)
Openness					.000(.000)	.002(.002)
Topic 2 (T2)	.005(.001)***	.005(.001)***	.005(.001)***	.005(.001)***	.005(.001)***	.005(.001)**
Topic 3 (T3)	.002(.001)	.002(.001)	.002(.001)	.002(.001)	.002(.001)	.002(.001)
Extraversion* T.2	.002(.001)					-.000(.001)
Extraversion * T.3	.001(.001)					-.173(.002)
Neuroticism * T.2		-.004(.001)**				-.004(.002)
Neuroticism * T.3		-.003(.001)*				-.004(.002)
Agreeableness* T.2			.001(.001)			-.001(.002)
Agreeableness* T.3			.001(.001)			.000(.002)
Conscient.* T.2				.002(.001)		.002(.001)
Conscient.* T.3				.001(.001)		.001(.001)
Openness * T.2					.000(.000)	.002(.002)
Openness* T.3					.000(.000)	.002(.002)
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
Cohen's *d* (Marg.R^2/Cond.R^2)	.35 / 2.67 (small/large)	.35 / 2.67 (small/large)	.28 / 2.61 (small/large)	.46 / 2.61 (small/large)	.35 / 2.61 (small/large)	.59 / 2.73 (medium/large)

*Note: * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p*-values were corrected in the full model by Benjamini-Hochberg (Benjamini & Hochberg, 1995) FDR procedure. T.2 = Topic 2, bodily perception/sensory life; .= Topic 3, socio-emotional life. E=Extraversion, N=Neuroticism, A=Agreeableness, C/Conscient. = Conscientiousness, O=Openness. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled.

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

	M1. E	M2. N	M3. A	M4. C	M5. O	M6. Full model
Predictors	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)	Estimate (*SE*)
Intercept	11.40(.319)***	11.40(.319)***	11.40(.319)***	11.40(.319)***	11.40(.319)***	11.40(.308)***
Extraversion	-.219(.321)					-.346(.383)
Neuroticism		.089(.320)				-.202(.379)
Agreeableness			-.030(.322)			-.027(.347)
Conscientiousness				-.328(.320)		-.342(.332)
Openness					.249(.319)	.413(.351)
Topic 2 (T2)	.731(.317)*	.731(.315)*	.731(.318)*	.731(.318)*	.731(.318)*	.731(310)
Topic 3 (T3)	.728(.317)*	.728(.315)*	.728(.318)*	.728(.318)*	.728(.318)*	.728(.310)
Extraversion* T.2	.355(.317)					.058(.385)
Extraversion * T.3	-.048(.317)					-.675(.385)
Neuroticism * T.2		-.489(.315)				-.493(.381)
Neuroticism * T.3		-.631(.315)*				-1.089(.381)*
Agreeableness* T.2			.095(.319)			-.124(.349)
Agreeableness* T.3			.114(.319)			-.093(.349)
Conscient.* T.2				.175(.318)		.043(.334)
Conscient.* T.3				-.086(.318)		-.245(.334)
Openness * T.2					.197(.318)	.248(.352)
Openness* T.3					.269(.318)	.592(.353)
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
Cohen's *d* (Marg.R^2/Cond.R^2)	.28 / 2.08 (small/large)	.35 / 2.12 (small/large)	.28 / 2.08 (small/large)	.28 / 2.08 (small/large)	.35 / 2.08 (small/large)	.63 / 2.17 (medium/large)

*Note: * indicates p < .05. ** indicates p < .01. ***indicates p <.000. p*-values were corrected in the full model by Benjamini-Hochberg (Benjamini & Hochberg, 1995) FDR procedure. T2 = Topic 2, bodily perception/sensory life; T3 = Topic 3, socio-emotional life. E=Extraversion, N=Neuroticism, A=Agreeableness, C/Conscient. = Conscientiousness, O=Openness. In all models, Determinism is the response variable. ICC = Intra-class Correlation Coefficient. AIC = Akaike's Information Criterion (lower values indicate better fit). Personality traits were centered and scaled.

Table 10.
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
Cohen's *d* (R^2)	.51 (medium)	.29 (small)	.35 (small)	.70 (medium)

*Note: * indicates p < .05. ** indicates p < .01. ***indicates p <.000.* Number of observations = 103 (two missing values). Predictors are centered and scaled.