**Is Temporal Continuity Shared by the Brain and Self? A Combined Behavioral-EEG
Study**

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A thesis submitted to the Faculty of Graduate and Postdoctoral Affairs in partial fulfillment of
the requirements for the degree of Master of Cognitive Science

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Abstract

The mechanisms connecting brain activity to mental features such as the self have long been of interest in both philosophy and neuroscience. Recently, the “common currency” hypothesis has suggested that the transformation from neural to mental activity presupposes an underlying feature shared between them. This common feature is broadly assumed to be the dynamics of time and space, with different temporospatial mechanisms underpinning specific mental contents. The current study tests the validity of this theory using the temporospatial dynamics of self as an instantiation of common currency. Since a key feature of the self is its ability to operate across different timescales, temporal continuity is hypothesized as a bridge between the neural level of the brain and the psychological level of the self. To test this hypothesis, EEG data was collected while participants listened to their own eight-minute, pre-recorded autobiographical narrative and that of a stranger in a counterbalanced order. Participants continuously evaluated each narrative’s contents as positive or negative by moving a mouse cursor relative to the centre of the computer screen. This resulted in concurrent neural and behavioral time series amenable to analysis using identical empirical measures of temporal continuity. Results showed larger values for select measures of continuity in response to the self-narrative (as distinct from the non-self narrative) for both EEG and behavior; however, there was no 1:1 correspondence between the two modalities. Together, our data show the utility of the common currency hypothesis but, at the same time, the need for more granular specification in the future.

Acknowledgements

First, I would like to thank my supervisor and mentor, Dr. Georg Northoff. Your guidance and support throughout this research project have been invaluable. I am incredibly grateful for the opportunity to explore the connection between brain and mind under your supervision.

Dr. Andrew Brook, thank you for helping me navigate the complexities of graduate studies as my co-supervisor, and also for your conceptual comments in support of this experiment. Dr. Rebecca Merkley, thank you for your willingness and interest in becoming involved in this project as a thesis committee member. I greatly appreciate your time and input.

I also would like to extend my gratitude to Dr. Annemarie Wolff and Julia Ignaszewski. Dr. Wolff, your technical expertise is greatly appreciated, and I am fortunate to have had your valuable support with my EEG analysis. Julia, thank you for your contributions during the early phases of this project.

Completing this thesis would not have been possible without the support of my family and friends. Jamie, my wife, I am grateful that we had the opportunity to navigate graduate school together. I owe much of this journey to your advice and support. To my parents, Brian and Kathy. Brian, thank you for always showing genuine interest in my research and for being willing to listen to, and critique, my ideas. Kathy, thank you for offering frequent home-made meals and dog-sitting services in times of stress. To Katelan, Bill, and Collins. Your visits have been a much needed diversion from the rigors of academic life during a pandemic.

Finally, I would like to thank Maureen, Kevin, Andrea, and Avery for your continual support.

Table of Contents

Abstract.....	ii
Acknowledgement.....	iii
List of Tables.....	vii
List of Illustrations.....	viii
List of Appendices.....	ix
Introduction.....	1
Concepts of Self.....	2
Common Currency.....	3
Common Currency and the Self.....	5
Temporal Continuity and Scale-Free Dynamics.....	7
Scale-Free Measurement.....	8
Empirical Support.....	12
EEG and fMRI Research.....	12
Behavioral Research.....	15
Gap in the Literature.....	16
Hypotheses.....	17
Materials and Methods	17
Subjects.....	17
Paradigm.....	17
Exploratory Psychological Scales.....	20
Behavioral Analysis.....	21
Cursor Distance.....	21
Power-Law Exponent.....	22
Detrended Fluctuation Analysis.....	22
Autocorrelation Window.....	22
Median Frequency.....	23
Lempel-Ziv Complexity.....	23
Electrophysiological Recording.....	23
Neuronal Analysis.....	24

Power-Law Exponent.....	24
Detrended Fluctuation Analysis, Autocorrelation Window, and Lempel-Ziv Complexity.....	24
Median Frequency.....	24
Alpha and Theta Peak Frequency.....	25
Band Power.....	25
Regions of Interest.....	25
Statistical Analyses.....	26
Results	27
Behavioral Data.....	27
Normality Assessment.....	27
Cursor Distance.....	27
Power-Law Exponent.....	28
Autocorrelation Window (ACW-50 and ACW-0).....	29
Detrended Fluctuation Analysis.....	30
Median Frequency.....	30
Lempel-Ziv Complexity.....	30
Neuronal Data.....	30
Whole Brain.....	30
Normality Assessment.....	30
Power-Law Exponent.....	31
Autocorrelation Window (ACW-50).....	33
Autocorrelation Window (ACW-0).....	33
Autocorrelation Window (ACW-0) Rest vs. Task.....	36
Detrended Fluctuation Analysis.....	36
Median Frequency.....	36
Lempel-Ziv Complexity.....	36
Alpha Peak Frequency.....	37
Theta Peak Frequency.....	37
Band Power.....	37

Cortical Midline.....	39
Normality Assessment.....	39
Power-Law Exponent.....	40
Autocorrelation Window (ACW-50).....	41
Autocorrelation Window (ACW-0).....	41
Detrended Fluctuation Analysis.....	41
Correlation Analysis.....	42
Brain and Behavior.....	42
Exploratory Correlation of Neuronal Values and Psychological Scales.....	42
Exploratory Correlation of Behavior Scales.....	44
Discussion	44
Neuronal Findings.....	42
Rest-Task Differences.....	45
Autocorrelation Window.....	47
Whole Brain and Cortical Midline.....	48
Behavioral Findings.....	49
Relationship Between Brain and Behavior.....	50
Common Currency.....	50
Input Processing and Outputs.....	51
Strengths, Limitations, and Future Research.....	54
Conclusion.....	55
References	56
Appendix A.....	71
Appendix B.....	73

List of Tables

Table 1. Shapiro-Wilk results, behavior.....	27
Table 2. Shapiro-Wilk results, whole brain.....	31
Table 3. Band power post-hoc analysis summary.....	38
Table 4. Band power descriptive statistics.....	39
Table 5. Shapiro-Wilk results, cortical midline.....	40
Table 6. Spearman correlations of brain and behavior.....	42
Table 7. Spearman correlations of neuronal values and psychological scales.....	43
Table 8. Spearman correlations of behavioral timeseries and scales.....	44

List of Illustrations

Figure 1. Schema of the common currency hypothesis.....	4
Figure 2. Scale-freeness of the power spectrum with temporal nestedness.....	8
Figure 3. Power-law exponent represented by the slope of a linear regression.....	9
Figure 4. Illustration of the detrended fluctuation analysis computation.....	11
Figure 5. The autocorrelation function.....	12
Figure 6. Schema of paradigm – study conditions.....	19
Figure 7. Schema of paradigm – cursor task.....	19
Figure 8. EEG montage and midline electrodes.....	26
Figure 9. Cursor distance from center.....	28
Figure 10. Power spectrum of self and non-self cursor distance.....	29
Figure 11. Power spectra by experimental condition.....	32
Figure 12. Autocorrelation plots by experimental condition.....	34
Figure 13. ACW-0 topoplots comparing rest and task.....	35
Figure 14. ACW-0 topoplots comparing experimental conditions.....	35
Figure 15. Band power by experimental condition.....	38

List of Appendices

Appendix A.....	71
Appendix B.....	73

Is Temporal Continuity Shared by the Brain and Self? A Combined Behavioral-EEG Study

The mechanisms connecting the brain and mind have long been the subject of philosophical inquiry. For instance, Leibnitz (1714) famously proposed that if one were to enter a sentient machine as if walking through a mill, they would notice components interacting but never see anything that could account for the machine's subjective experience. More recently, the mind-body problem has also been explored with neuroscientific methods. However, despite scientific advancements in neuroimaging techniques such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET), it remains unclear how neuronal activity engenders mental features such as consciousness and the self. Among various models and hypotheses, the “common currency” hypothesis (Northoff et al., 2020; Kolvoort et al., 2020) has suggested that the transformation from neural to mental activity presupposes an underlying feature shared between them. This common feature is broadly assumed to be the dynamics of time and space, with different temporospatial mechanisms underpinning specific mental contents.

The current investigation tests the validity of this theory using the temporospatial dynamics of self as an instantiation of common currency. To this end, participants continuously evaluated self-relevant and non-self-relevant audio recordings using a mouse cursor while EEG data was collected. Our first hypothesis is that measures of temporal continuity will exhibit larger values in response to self-relevant stimuli when compared to non-self-relevant information in both EEG and behavioral data. If supported, positive correlations between respective measures across modalities should also be observed.

This paper will begin by briefly discussing some conceptualizations of the self that illustrate the need for an intrinsic connection with the brain. Second, we present our rationale for considering temporal continuity as a viable candidate for a common currency between the neuronal and mental levels of self. Third, we introduce the concept of scale-free dynamics as an index of temporal continuity. Fourth, we provide empirical support for an association between scale-free dynamics and the self. Finally, examinational findings and their implications are discussed in the context of relevant literature.

Concepts of Self

The self is a core feature of mental life. William James (1890) viewed the self as the most basic unit of analysis for a psychological science, stating that other problems of the mind are sequelae of this most fundamental issue. Yet, despite its centrality, there are myriad conceptualizations of the self, and there is no agreed upon definition in philosophy or cognitive science. For instance, Gallagher (2000) describes the narrative self and minimal self. The narrative self is temporally extended by past memories and projections into the future. It is a persisting self-concept or sense of identity over time that is shaped through the stories we tell ourselves or that others tell of us. In contrast, the minimal self refers to a primitive sense that I exist as the subject of my own experience in the immediate and ‘specious present.’ It is what remains when all the peripheral components of self are discarded.

William James (1890) famously introduced the dichotomy between self as subject (“I”) and self as object (“Me”). As an illustration, the self as object, also referred to as the empirical self, is exhibited while I think about my physical attributes or personality traits; the one who thinks about the physical attributes is the self as subject. James further elaborates on the empirical self by subdividing it into its material, social, and spiritual components. The material

self refers to the body or any other place or object that the individual considers to be ‘mine’; the social self describes facets of our identity and behavior that may change according to social circumstances; in contrast, the spiritual self includes aspects of our identity such as personality and moral values.

Furthermore, Neisser (1988) describes the self in its ecological, interpersonal, extended, private, and conceptual dimensions. Neisser (1988) argues that the phenomenological experience of self tends to be unified because its aspects are bound together by various types of stimulus information. Regardless, each aspect has different developmental trajectories, is susceptible to different pathological states, and adds a unique element to our overall experience.

Common Currency

The aforementioned conceptualizations are only a choice selection as there are manifold philosophical and psychological models of self (see Gallagher & Daly, 2018 for an overview). However, a common deficiency in these models is the lack of any necessary or intrinsic connection between the brain and mind. The “common currency” hypothesis has recently addressed this issue by offering a theoretical framework whereby the transformation from neural to mental activity presupposes an underlying feature shared between them (Northoff et al., 2020; Kolvoort et al., 2020).

This feature is broadly assumed to be the dynamics of the brain’s “inner time and space” (i.e., spatiotemporal dynamics) understood in terms of how the brain constructs its own intrinsic spatial and temporal relationships through for instance functional connectivity and frequency fluctuations, respectively (Northoff et al., 2020; see Figure 1). The theory posits that different temporospatial mechanisms, through structuring and organizing cognitive functions, engender specific cognitive or mental contents (Kolvoort et al., 2020; Northoff et al., 2020). As such, the

common currency hypothesis can accommodate many aspects of mental life, including the self. We will further explain the concept of spatiotemporal dynamics and then provide some examples of how each of these pertains to the self as a common currency.

Figure 1

Schema of the common currency hypothesis

Note. Figure obtained from Northoff et al. (2020).

The term ‘spatiotemporal dynamics’ can be decomposed into its two constituent parts: spatial topography and temporal dynamics. The former refers to the spatial organization of the brain and relationships between its parts and how that influences the character of mental activity. For instance, functional connectivity (FC) is a statistical property of brain activity that describes temporally synchronous neuronal events between anatomically distinct brain regions (Friston, 1994). An fMRI study by Tagliazucchi (2016) demonstrated a relationship between FC and the self; they found that subjective reports of ego dissolution following lysergic acid diethylamide

(LSD) consumption were associated with increased global functional connectivity. The relevance of spatial topography for mental features is also evident when considering that many studies have shown a connection between cortical midline structures (CMS) and the self (Northoff & Bermpohl, 2004; Northoff et al., 2006; van den Meer et al., 2010; Qin & Northoff, 2011; Murray et al., 2015; Huang et al., 2016; Wolff et al., 2019). Temporal dynamics, in contrast, refers to the time-frequency properties of neural activity such as the relationship between power and frequency.

The central notion of the common currency hypothesis is that these spatiotemporal dynamics are analogously present on the mental level. For instance, there is some evidence to suggest that the speed of neuronal activity in the sensory motor network and visual network, operationalized as variability, may serve as a template for our experience of “inner time” and “outer time,” respectively (Northoff et al., 2018). The relative balance of neuronal speed between these regions may determine whether we perceive the passage of time as either too slow or fast on a psychological level. Time speed may therefore serve as one form of common currency that connects the neural and mental levels (Northoff et al., 2018, 2020; Kolvoort et al., 2020).

Common Currency and Self

What are the spatiotemporal features that are relevant for the self? A key temporal characteristic of the self is its ability to operate across multiple timescales. This is supported by the observation that our bodies and environment continuously change, while the self remains stable and provides temporal continuity (Marks-Tarlow, 1999; Kolvoort et al., 2020; Ersner-Hershfield et al., 2009a, 2009b). Furthermore, continuity is related to what Sui and Humphreys (2015) describe as an “integrative self model” or the “integrative function of self”. This refers to how the self modulates behavior related to various functions such as reward (Yankouskaya et al.,

2020), decision making (Nakao et al., 2019), and perception (Sui et al., 2012). The integrative function of self may operate by assimilating the different time points associated with the various functions. For instance, sensory perception and decision making will naturally occur over different timescales, and these can be connected and integrated by the self through its temporal continuity that extends beyond the respective timescales of either function (Northoff et al., 2020).

Marks-Tarlow (1999, 2002) proposed a hierarchical model of the self that is highly relevant for our discussion of temporospatial continuity. According to Marks-Tarlow (1999), the self is a multifaceted construct with each of its levels being shaped by complex interactions with other components. The biological, psychological, and social levels are emergent, and each level becomes embedded or integrated within the next. This results in fractal properties such as self-organization, bidirectional feedback loops, and interactions across permeable boundaries.

Marks-Tarlow (1999) therefore proposes that the self exhibits fractal organization and provides illustrations of this from her clinical experience as a psychologist. For example, a patient referred to as Mr. O was reluctant to meaningfully engage with his own emotions on an intrapersonal level. Likewise, this difficulty manifested on an interpersonal level as a fear of confronting difficult emotions in his marriage which ultimately caused problems with intimacy. This fractal organization of the self necessarily implies continuity, in a hierarchical sense, as the characteristics of lower-levels are observed in subsequent levels of the self without interruption.

Taken as a whole, we believe there are strong conceptual reasons for associating temporal continuity with the self. We therefore hypothesize that continuity, which is closely related to fractal organization, may be the relevant temporospatial feature that can serve as one bridge or

common currency between the brain and self. The relationship between fractal self-similarity and continuity will first be illustrated in a discussion of scale-free dynamics.

Temporal Continuity and Scale-Free Dynamics

Many processes in nature do not have a characteristic scale, and as such, cannot be described properly with measures of central tendency such as the mean or median. These systems are appropriately referred to as “scale-free” or “scale-invariant” (Hardstone et al., 2012). For instance, *Romanesco broccoli* does not have a characteristic flower size on the cauliflower; the flower size is better represented as a power-law function stating that the size of flower is inversely proportional to its frequency of appearance (Hardstone et al., 2012). Similarly, the brain’s spontaneous activity exhibits a prominent $1/f$ component as power declines with increasing frequency. This is expressed as $P \propto 1/f^\beta$, where P is power, f is frequency, and β is referred to as the power-law exponent (He et al., 2010; He, 2014). Importantly, the relationship between power and frequency is maintained across different temporal scales. When log-transformed frequency and power are plotted, the arrhythmic activity approximates a straight line whose slope is roughly the same regardless of frequency range (He et al., 2010).

This is illustrated in Figure 2 which zooms into smaller and smaller subsections of the power spectrum while still exhibiting the same approximate shape. As such, the relationship between power and frequency can be characterized as being scale-free and therefore fractal or self-similar (He et al., 2010; He, 2014). Fractal organization in the frequency domain implies temporal nestedness with slower, powerful frequencies containing the faster, weaker ones. This results in long-range temporal correlations (LRTC) as these lower frequencies with their long wavelengths exert influence and a degree of stability over future neural dynamics (Linkenkaer-Hansen et al., 2001; Northoff & Huang, 2017).

Figure 2

Scale-freeness of the power spectrum with temporal nestedness

Scale-Free Measurement

There are numerous methods available to probe for scale-free activity within a signal. Implementing more than one type of fractal analysis is recommended because each has its own respective strengths and weaknesses (Stadniski, 2012). The use of any single method in isolation therefore lacks the descriptive power necessary to avoid incomplete or misleading interpretations of the data (Rangarajan & Ding, 2000). Scale-invariant activity can be directly measured in the frequency domain by the power-law exponent (PLE) or the temporal domain using detrended fluctuation analysis (DFA). It is also possible to indirectly probe scale-invariance temporally with the autocorrelation function (ACF).

As previously discussed, the PLE is the slope of a linear regression between log power and log frequency and therefore represents the relationship between power and frequency (see Figure 3). An exponent of zero would indicate the lack of any structure – such is the case with white noise (He, 2014). Higher PLE values reflect a more complex temporal organization characterized by nested frequencies and LRTC (He, 2014). For instance, the amplitude modulation of oscillations in a neuronal timeseries tend to exhibit β values significantly larger than zero but less than one; this is considered to indicate the presence of LRTC (Nikulin et al., 2012; Rangarajan and Ding, 2000; Linkenkaer-Hansen et al., 2001, 2007; Nikulin & Brismar, 2005; He et al., 2010; Smit et al., 2013; Kello et al., 2010).

Figure 3

Power-law exponent represented by the slope of a linear regression

DFA indexes the power-law scaling of oscillatory fluctuations as a function of different window sizes (Hardstone et al., 2012). This is achieved by first calculating a cumulative sum of the signal whereby each consecutive data point is iteratively summed with the one preceding it. Then, a set number of logarithmically spaced window sizes or scales are selected ranging between a minimum of four samples to the length of the signal. For instance, we may select 20

different window sizes with the first and last being 10 seconds and 120 seconds, respectively.

For each of these scales, the signal is epoched according to the window size (e.g., the data is split into 10 second segments for the first scale with the segment size expanding for additional scales).

These epochs are detrended and the root mean square (RMS) is computed (i.e., mean fluctuation). This process is repeated for each window size. Finally, the complete series of RMS values is plotted against the window sizes on a logarithmic scale. A linear regression is calculated between log-RMS and log-scales with the slope representing the DFA exponent which is an estimate of the Hurst parameter (Hardstone et al., 2012; see Figure 4). A DFA exponent of $\alpha > 0.5$ indicates positive correlations in the signal and larger fluctuations over the longer window sizes than you would predict in random, white noise ($\alpha = 0.5$). Therefore, $\alpha > 0.5$ suggests that the signal is exhibiting LRTC (Hardstone et al., 2012).

Figure 4

Illustration of the detrended fluctuation analysis computation

Note. Figure obtained from Hardstone et al. (2012).

The ACF correlates a signal with itself over its own time course, that is, copies of itself that are temporally shifted with a series of lags (Murray et al., 2014; Honey et al., 2012; SanCristobal et al., 2021). Crucially, the degree of autocorrelation decays over time as the number of lags increases. A common practice in EEG and MEG studies is therefore to report the autocorrelation window (ACW) representing the number of lags at 50 percent of the maximum ACF value (i.e., ACW-50; Raut et al., 2020; Watanabe et al., 2019; Ito et al., 2020; Honey et al., 2012). Worth noting, however, Golesorkhi et al. (2021) introduced the novel variant ACW-0

based on the number of lags where the ACF reaches zero (see Figure 5). The ACF and its derivative measures therefore index the degree to which previous activity predicts future dynamics over multiple timescales (Golesorkhi et al., 2021; Honey et al., 2012).

Figure 5

The autocorrelation function

Note. Figure adapted from Golesorkhi et al. (2021).

In any case, high PLE, DFA, and ACW values indicate higher degrees of LRTC, while lower values suggest that only the most recent time intervals influence future events. Scale-invariance and LRTC are thus highly relevant for our discussion of temporal continuity as they provide different kinds of operationalizations of it by measuring the degree to which faster frequencies are nested within, and are affected by, the slower frequencies.

Empirical Support

EEG and fMRI Research

Studies have found a connection between measures of scale-free brain activity and mental features such as the self. For instance, an EEG study by Wolff et al. (2019) explored the relationship between spontaneous brain activity and self-consciousness. Fifty participants in the

study completed a five minute resting state session and were then administered the Self-Consciousness Scale (SCS; Abe et al., 1996; Fenigstein et al., 1975; Scheier & Carver, 1985). The SCS is a 20 item questionnaire that quantifies the private, public, and social dimensions of self. Private self-consciousness refers to our tendency to reflect upon ourselves through introspection; public self-consciousness concerns an awareness of how others view us, and the social dimension measures social anxiety. While there was no correlation between resting-state PLE and the public or social subscales, Wolff et al. (2019) found a significant correlation between PLE and private self-consciousness.

This finding was corroborated by Huang et al. (2016) in fMRI. Participants in this study completed a six minute resting-state scan and then responded to the SCS as described above. PLE values were then extracted from spontaneous activity in the medial prefrontal cortex (MPFC) and posterior cingulate cortex (PCC), two key structures of the cortical midline. The results showed a significant correlation between PLE in these brain regions and private, but not public or social self-consciousness.

Scale-free activity in fMRI has also been shown by Scalabrini et al. (2019) to predict task-evoked neural response to animate rather than inanimate stimuli. Participants in the study completed a resting session and then touched a real hand or a mannequin hand. The authors found that animate and inanimate discrimination during the task was correlated with resting-state PLE in the perigenual anterior cingulate cortex (PACC). This is relevant, albeit indirectly, because participants reported the animate stimulus to be closer in space, have greater relevance, and higher temporal synchronicity to the self than an inanimate stimulus.

A further resting-state fMRI study by Lei et al. (2013) explored the link between scale-free properties of spontaneous brain activity and aspects of personality. Following a five-minute

resting state session, participants were administered the Eysenck Personality Questionnaire – Revised Short Scale (EPQ-RSC) to assesses extraversion and neuroticism. The results indicated that higher Hurst parameter estimates (an index of scaling properties) in the default mode network (DMN) were negatively correlated with extraversion scores on the EPQ-RSC. There was no significant correlation observed between scale-freeness and neuroticism.

Higher resting state PLE and ACW in EEG recordings have also been linked to a stronger self-prioritization effect (Kolvoort et al., 2020). Subjects were required to engage in a matching task that involved associating the self, non-self, and celebrities with a geometric shape during the training phase. They had to identify the correct pairings in the experiment’s task phase as shapes and labels were presented with or without an interval delay between them. Notably, there was a significant positive correlation between neuronal PLE and ACW with the degree of self-prioritization effect observed across temporal delays. Kolvoort et al. (2020) therefore suggest that integration on the neuronal level relates to psychological integration of self-relevant stimuli on the psychological level.

Together, these studies demonstrate the relevance of temporal continuity in the brain for various facets of the self. This only satisfies half of the common currency assumption, however, as the psychological level remains unexamined: do psychological processes related to the self exhibit a temporal continuity more or less analogous to that on the neuronal level? To address this, we need to identify studies that have applied similar measures of continuity to timeseries data that reflect psychological functions or characteristics of the self.

Behavioral Research

Wong et al. (2014), for instance, demonstrated a connection between the self and fractal properties of a behavioral timeseries. They had subjects record an autobiographical narrative and subsequently evaluate its emotional valence on a moment-to-moment basis by positioning a mouse-cursor on the computer. The authors developed a composite fractal parameter consisting of PLE, DFA, signal summation conversion, and Whittle estimation of the Hurst coefficient. The degree of self-similarity in the continuous behavioral time series correlated with scores on the Self Concept Clarity (SCC) scale.

This study supports earlier findings by Delignieres et al. (2004) who observed a relationship between longitudinal self-esteem data and fractional Brownian motion. The researchers had four participants complete the Physical-Self Inventory (PSI-6; Ninot et al., 2001) twice per day over a period of 512 days. This resulted in a time series of 1024 data points for each individual based on the daily PSI-6 global self-esteem scores. The PLE or β exponent hovered slightly above 1.0 for most participants which is indicative of $1/f$ behavior and long-term memory in the system. An estimate of the Hurst (H) parameter using rescaled range analysis (R/S) yielded values between 0.18-0.40 suggesting anti-persistent LRTC. Similar estimates of H were obtained using dispersional analysis which is the linear regression between log-transformed standard deviation and interval length. This provided further evidence of LRTC in the self-esteem time series.

Finally, longitudinal self-esteem scores have also been investigated using the autocorrelation function. Fortes et al. (2004) followed seven participants who recorded data related to global and physical self-esteem for 228 days. They found significant autocorrelations

in some of the time series up to 100 lags. This is indicative of long-term memory (LRTC) or temporal continuity within the signal.

Gap in the Literature

These studies investigated the connection between self and indices of temporal continuity (i.e., PLE, DFA, ACW) by relating EEG and fMRI data to psychological scales or discrete tasks. Alternatively, some of the aforementioned research analyzed the fractal properties of scales or behavior over time. While all of these studies provide empirical support for a connection between scale-freeness or temporal continuity and the self, a direct approach to exploring temporal continuity as a common currency for the neuronal and psychological levels would require that identical empirical measures be applied to neural and behavioral timeseries recorded concurrently

Although third-person, scientific investigations necessarily preclude the possibility of directly quantifying the mind or any ‘mental timeseries’ as such, we can, as a proxy, use a continuous behavioral task whose output reflects mental activity in the form of self-referential processing. Our present focus is therefore on the connection between brain and behavior. A demonstrable empirical relationship between them would support the common currency hypothesis and open the possibility for speculations about the relationship between brain activity and self on a psychological level.

While our primary objective is to identify a bridging mechanism between brain and behavior, the current experiment fills a gap in both the common currency and self-referential processing literature. There is a significant corpus exploring the neural correlates of self-referential processing in EEG (see Knyazev, 2013). However, to our knowledge, no studies have

investigated the connection between neural and psychological indices of temporal continuity while processing self-relevant information.

Hypotheses

We reviewed empirical studies demonstrating a connection between temporal continuity and the self in both EEG and behavior. Given this relationship, we expect to find significantly higher behavioral and neuronal PLE, DFA and ACW values while participants are exposed to self- rather than non-self-relevant information. Furthermore, we predict significant positive correlations between each of these measures and their respective EEG and behavioral analogs.

Materials and Methods

Subjects

Twenty-seven (10 females; mean age = 30.3) healthy subjects were recruited from the local community in Ottawa, Canada. All participants were right-handed per the Edinburgh Handedness Tool (Oldfield, 1971). The study lasted approximately three hours and subjects were compensated for their parking expenses at The Royal Ottawa's Institute for Mental Health Research. The experimental protocol was approved by the ethics commission (REB #2016004) of the University of Ottawa Institute of Mental Health Research and all participants provided written consent prior to engaging in any study-related activities.

Paradigm

Our experiment used a behavioral paradigm modified from Vallacher et al. (2002). Participants in their study first recorded an autobiographical narrative (average length 2 min 52 sec) and were then presented with that recording during the task phase of the experiment. Subjects continuously evaluated the narrative's contents as positive or negative using a mouse cursor. On a moment-to-moment basis, they indicated degrees of negativity or positivity by

moving the cursor either away from the center or towards the center of the screen, respectively. The researchers computed: descriptive statistics of the cursor distance from center; velocity of cursor movements; cursor acceleration; and, time spent at rest which they then correlated with a small number of psychological scales.

The current paradigm expands upon this original template. Participants in our study recorded an unstructured, eight-minute autobiographical narrative using freely available audio recording software on a laptop. Participants were encouraged to be as comprehensive as possible and discuss any aspects of themselves and their lives that they deemed important. After completing an eight minute, eyes-open resting state session, subjects were presented with their prerecorded narrative and that of a stranger through headphones in a counterbalanced order (see Figure 6). Following the Vallacher et al. (2002) methodology, subjects indicated degrees of negativity or positivity on a moment-to-moment basis by positioning the mouse cursor relative to the center of the screen. The color of the circle became green or red as participants moved their cursor towards the center to indicate positivity or towards the periphery to indicate negativity, respectively. Neutral or intermediate positions were represented by yellow (see Figure 7). The colors served to remind participants that each cursor position held an emotional valence.

Figure 6*Schema of paradigm – study conditions* **Figure 7***Schema of paradigm – cursor task*

The primary dependent variable was cursor distance from the center of the screen measured in pixels sampled at 200 Hz. In contrast to Vallacher et al. (2002), our study assessed cursor distance from the center along both x- and y-axes rather than just the former. This dual-axis feature allowed participants to interface with computer program freely without having to constrain their movements. Ultimately, our modifications to the Vallacher et al. (2002) paradigm combined with EEG yielded concurrent neural and behavioral time series that are amenable to analysis with identical empirical measures.

Exploratory Psychological Scales

Following the behavioral task, subjects completed the Edinburgh Handedness Inventory (Oldfield, 1971) and an in-house health questionnaire to ensure they were right-handed and free of medical complications that might adversely affect EEG recording quality (see Appendix A). Participants also completed a battery of psychological scales to determine how the structure of self relates to the behavioral and neuronal measures; however, the scales were deemed to be of an exploratory nature due to the small sample size. We adopted this approach based on Vallacher et al. (2002) and Wong et al. (2014) who both correlated a limited number of scales with cursor dynamics. The former assessed participants using the Rosenberg Self Esteem Scale (RSES; Rosenberg, 1965), the Self- Concept Clarity (SCC; Campbell et al., 1996) scale, the Rosenberg Stability Scale (1965), and a custom measure of self-concept certainty that asked participants how certain they felt about aspects of their identity (Vallacher et al., 2002). In contrast, Wong et al. (2014) focused entirely on relating cursor movements to the SCC.

Participants in our study completed a more comprehensive range of inventories. These were the: (a) RSES, assessing global self-esteem; (b) Instability of Self Esteem Scale (ISES; Chabrol et al., 2006), exploring changes in self-esteem over time; (c) SCC, measuring the coherence of self-concept and its stability; (d) Self Consciousness Scale (SCS-R; Abe et al., 1996; Fenigstein et al., 1975; Scheier & Carver, 1985), evaluating how attention is directed towards private or public aspects of self; and (e) the Pathological Narcissism Inventory (PNI; Pincus et al., 2009), used to identify narcissistic tendencies.

Subjects were also administered the: (f) Childhood Trauma Questionnaire (CTQ; Bernstein et al., 2003), containing items about whether participants have experienced different forms of childhood abuse; (g) Beck Depression Inventory (BDI-II; Beck et al., 1996), used for

evaluating depressive symptoms; (h) Zimbardo Time Perspective Inventory (ZTPI; Zimbardo & Boyd, 1999), to assess the emotional valence that participants impute to past, present, or future; and (i) the New York Cognition Questionnaire (NYCQ; Gorgolewski et al., 2014), which categorizes and quantifies spontaneous thoughts during a rest session.

Behavioral Analysis

PLE, DFA, and ACW were the primary measures of interest for the behavioral timeseries. In addition, we calculated median frequency (MF) and Lempel-Ziv complexity (LZC). The MF describes the frequency corresponding to the median power value - half the power lies above and below this point (Tonner & Bein, 2006). Lower median frequencies are expected with higher PLE and ACW values because of the relatively high power in slower frequency ranges. LZC measures the compression of information as the number of unique subsequences in a time series. Fewer sequences are indicative of low complexity or compression while having many unique sequences implies higher compression (Aboy et al., 2006). We include this measure since the paradigm involves a continual exchange of information to and from the participant; however, a specific relationship with the scale-free indices is unclear.

One participant was excluded from the behavioral analysis due to a corrupt non-self data file (n=26). All behavioral files were truncated to 470 s to mirror the EEG recording length, described below.

Cursor Distance

The average cursor distance from the center of the screen in pixels was calculated for each subject during the self and non-self conditions. Consequently, two separate ‘distance’ values were generated for each subject.

Power-Law Exponent

The power spectral density (PSD) was first calculated using the Welch method in Python MNE (version 0.22.1; Gramfort et al., 2013). Briefly, Welch PSD segments the signal into windows, computes a Fourier transform on each, and averages the windows together yielding a final periodogram (Welch, 1967). The window size was 1000 timepoints with 50 percent overlap using a Hann windowing function. These parameters were selected as they produced a power spectrum with an optimal balance between resolution and noise. A linear regression was then calculated between the log-transformed power and frequency arrays using ‘polyfit’ from Python’s Numpy package. The slope of this regression was extracted as the PLE. Goodness of fit for the regression was estimated using r^2 values.

Detrended Fluctuation analysis

DFA was calculated in Python using the Fathon package (Bianchi, 2020). The default parameters were used as these conform to the guidelines established by Hardstone et al. (2012). Specifically, logarithmically spaced window sizes were selected with a lower bound of four samples and an upper bound of ten. However, contrary to Hardstone et al. (2012), we opted against having overlap between the windows in order to reduce computational demands.

Autocorrelation Window

An autocorrelation function was first calculated in Python with the Statsmodel library (Seabold & Perktold, 2010) using a fast Fourier transform algorithm. The ACW-50 and ACW-0 variants were then computed as the first lags where the ACF decays to 50 percent of its maximum value, and zero percent (see Golesorkhi et al., 2021), respectively.

Median Frequency

Power spectral density (PSD) was first calculated using the Welch method in Python MNE (version 0.22.1; Gramfort et al., 2013). As with PLE, the window size was 1000 timepoints with 50 percent overlap and a Hann windowing function. The frequency corresponding to the median power value was identified using a custom script.

Lempel-Ziv Complexity

An in-house Python script was developed according to the methods of Ziv and Lempel (1977) that calculated the number of unique subsequences after normalizing the signal relative to the number of data points.

Electrophysiological Recording

EEG data was obtained using a 64-channel Brain Vision Easycap (International Ten-Twenty System) with Ag/AgCl electrodes referenced to the right mastoid. Impedance for each electrode was under 5 k Ω and the sampling rate was 1000 Hz with DC recording. Preprocessing was performed using an in-house MATLAB script relying upon functions from the EEGLAB toolbox (version 2021; Delorme & Makeig, 2004). The data was first down sampled to 500 Hz followed by high and low pass filters at 0.5 and 50 Hz, respectively. Channels were spherically interpolated if they were flat for at least five seconds or if the activity exceeded three interquartile ranges. All channels were then re-referenced to the average prior to an independent component analysis (ICA) yielding 62 ICs. Finally, components were rejected by implementing the Multiple Artifact Rejection Algorithm (MARA; Winkler et al., 2011).

Four participants were excluded from the EEG analysis due to excessive noise and one was removed for technical issues associated with data acquisition. Although subjects were instructed to record an eight-minute autobiographical narrative, there were minor discrepancies

in recording length. To account for this, each timeseries was truncated to 470 s to match the length of the shortest recording.

Neuronal Analysis

The behavioral analysis was replicated in the EEG data. However, there were some notable differences. First, alpha peak frequency (APF) and theta peak frequency (TPF) were calculated, representing the frequencies corresponding to the maximum power values observed in their respective bands (Gutmann et al., 2015). Both APF and TPF were included since previous studies have noted that changes in alpha and theta activity are related to self-referential thoughts (Knyazev et al., 2012). Second, average band power was calculated from the PSD. Finally, neuronal data was collected at rest in addition to the task conditions.

Power-Law Exponent

The PSD was calculating using Welch's method in Python MNE (version 0.22.1; Gramfort et al., 2013). Window sizes were 3200 timepoints with 50 percent overlap and a Hann windowing function. A linear regression was then calculated between the log-transformed power and frequency arrays using polyfit from Python's Numpy package. The slope of this regression is the PLE. Goodness of fit for the regression was estimated using r^2 values.

Detrended Fluctuation Analysis, Autocorrelation Window, and Lempel-Ziv Complexity

The DFA, ACW-50, ACW-0, and LZC were computed for each electrode using the same scripts and parameters described for the behavioral data. The average across all electrodes was obtained.

Median Frequency

The PSD was first calculated using the Welch method in Python MNE (version 0.22.1; Gramfort et al., 2013). Window sizes were 3200 timepoints with 50 percent overlap and a Hann

windowing function. For each electrode, the frequency corresponding to the median power value was identified and an average of all electrodes was then computed.

Alpha and Theta Peak Frequency

The PSD was first computed according to the methods employed for PLE and MF. The maximum power values were identified within the alpha and theta frequency bands. The frequencies corresponding to these maximum values were then extracted.

Band Power

We obtained the PSD per the steps previously indicated for PLE, MF, APF, and TPF. Although significant variation exists between studies regarding how frequency bands should be delineated (Newson & Thiagarajan, 2018), we isolated and defined the bands as follows: delta (1-5 Hz), theta (5-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and Gamma (30-50 Hz). The average activity across electrodes was then obtained for each subject.

Regions of Interest

A whole brain analysis was performed for each measure using the average of all electrodes. In addition, we applied our scale-free measurements (i.e., PLE, DFA, ACW) to the midline electrodes because of a priori assumptions regarding the relevance of cortical midline regions such as pACC and PCC for the self (Northoff & Bermpohl, 2004; Northoff et al., 2006; van der Meer et al., 2010; Qin & Northoff, 2011; Murray et al., 2015; Huang et al., 2016; Wolff et al., 2019). Specifically, the following electrodes were isolated and averaged together: AFp1, AFp2, FCz, Cz, OI1h, OI2h, CPz, Pz, FFC1h, FFC2h, CPP1h, CPP2h, FCC1h, FCC2h, CPP1h, CPP2h, AFF1h, AFF2h, PPO1h, PPO2h, POO1, and POO2 (see Figure 8).

Figure 8*EEG montage and midline electrodes* **Statistical Analyses**

Normality was assessed using the Shapiro-Wilk test. Paired-samples t-tests (2-tailed) were performed for behavioral measures approximating a normal distribution to compare self and non-self conditions. Wilcoxon sign-rank tests were employed when behavioral variables deviated considerably from normality. In EEG, we performed a repeated-measures ANOVA or the non-parametric Friedman test for each measure comparing average values between rest and task states. Post-hoc t-tests or Wilcoxon tests were calculated with Bonferroni correction following significant results. Finally, Spearman rank-order correlations were calculated to probe the relationship between brain, behavior, and psychological scale data.

Results

Behavioral Data

Normality Assessment

The Shapiro-Wilk test was performed to determine whether the behavioral data satisfied assumptions of normality. Normality was violated considerably for the majority of behavioral measures with the exception of cursor distance and PLE. The results of this assessment are summarized in Table 1, below.

Table 1

Shapiro-Wilk results, behavior

Variable	Test statistic	p-value
Cursor Distance Self	.970	.632
Cursor Distance Other	.957	.329

PLE Self	.922	.049
PLE Other	.921	.047

ACW-50 Self	.742	< .001
ACW-50 Other	.636	< .001

ACW-0 Self	.877	.005
ACW-0 Other	.844	.001

DFA Self	.808	< .001
DFA Other	.871	.004

MF Self	.252	< .001
MF Other	.279	< .001

LZC Self	.544	< .001
LZC Other	.750	< .001

Cursor Distance

Before considering the scale-free and ancillary measures, we first conducted a paired-sample t-test (2-tailed) comparing self and non-self cursor distances. As illustrated in Figure 9,

results indicate significantly larger cursor distances in the self ($M = 293.55$, $SD = 156.80$) compared to the non-self condition ($M = 215.25$, $SD = 124.06$), $t(25) = 3.45$, $p = .002$, 95% CI [31.59, 125.01]. This means that subjects moved the cursor farther from the center during the self-specific task when compared to the non-self-specific task. Furthermore, it shows that the self was evaluated more negatively than the non-self.

Figure 9

Cursor distance from center

Power-Law Exponent

The fractal analyses were then investigated beginning with the PLE. A paired-sample t -test (2-tailed) was performed to compare the average PLE between the self and non-self conditions. There was a significantly larger PLE observed in response to self-referential ($M = 2.10$, $SD = 0.09$, $r^2 = .791$) compared to non-self-referential ($M = 2.07$, $SD = 0.11$, $r^2 = .800$) processing, $t(25) = 2.282$, $p = .031$, 95% CI [0.003, 0.062].

Non-parametric results are also reported given that our Shapiro-Wilk test indicated a slight deviation from normality. A Wilcoxon signed-ranks test comparing self and non-self PLE replicated the parametric findings ($Z = -2.172, p = .030$). These results are visualized in Figure 10 below.

Figure 10

Power spectrum of self and non-self cursor distance

Autocorrelation Window (ACW-50 and ACW-0)

The autocorrelation function and its derivative measures (ACW-50 and ACW-0) were then investigated. A Wilcoxon signed-ranks test demonstrated a significant difference between self ($M=5913.08, SD=5463.58$) and non-self ($M=5556.31, SD=7113.74$) conditions with respect to ACW-50 values, $Z = -2.222, p = .026$.

In contrast, results showed no effect of condition for ACW-0 despite its naturally larger window sizes. The average window length in response to self-relevant inputs ($M=10366.04, SD=7871.10$) was not significantly larger than that in response to non-self-relevant information ($M=9459.31, SD=7912.47$), $Z = -1.359, p = .174$.

Detrended Fluctuation Analysis

Wilcoxon results for our final scale-free measure, DFA, did not indicate any significant difference between self ($M=1.69$, $SD=0.12$) and non-self ($M=1.70$, $SD=0.09$), $Z = -.190$, $p = .849$.

Median Frequency

Median frequency values were compared between conditions as an ancillary measure. A Wilcoxon signed-ranks test did not yield any difference in MF between self ($M=0.081$, $SD=0.065$) and non-self conditions ($M=0.076$, $SD=0.040$), $Z = -1.000$, $p = .317$.

Lempel-Ziv Complexity

Finally, using a Wilcoxon signed-ranks test, we did not observe any effect of condition for LZC values between self ($M=0.110$, $SD=0.011$) and non-self-narratives ($M=0.111$, $SD=0.006$), $Z = -1.004$, $p = .316$.

Neuronal Data

Whole Brain

Normality Assessment. The Shapiro-Wilks test was performed to determine whether the neuronal data were normally distributed. The repeated-measures ANOVA is robust to violations of the normality assumption (Schmider et al., 2010; Blanca et al., 2017), so we proceeded with the calculation in situations where deviations from normality were minor. For more severe cases, however, the Friedman test was performed as non-parametric alternative. The Shapiro-Wilk results are summarized in Table 2.

Table 2*Shapiro-Wilk test results, whole brain*

Variable	Test statistic	p-value
PLE Other	.934	.151
PLE Rest	.927	.107
PLE Self	.914	.058

ACW-50 Other	.852	.004
ACW-50 Rest	.883	.014
ACW-50 Self	.844	.003

ACW-0 Other	.967	.639
ACW-0 Rest	.966	.617
ACW-0 Self	.904	.035

DFA Other	.962	.531
DFA Rest	.963	.543
DFA Self	.966	.624

MF Other	.961	.507
MF Rest	.975	.815
MF Self	.979	.905

LZC Other	.902	.032
LZC Rest	.880	.012
LZC Self	.944	.239

APF Other	.899	.028
APF Rest	.915	.061
APF Self	.954	.373

TPF Other	.881	.013
TPF Rest	.883	.002
TPF Self	.862	.006

Power-Law Exponent. To explore whether temporal continuity serves a common currency between the neuronal and behavioral timeseries, we conducted a repeated-measures ANOVA comparing PLE between rest and task states (see Figure 11). There was a significant effect of experimental condition on PLE, $F(2, 42) = 21.579, p = < .001$. Mauchly's test did not

indicate any violation of sphericity, $X^2(2) = 2.579$, $p = .275$. Three paired-samples t-tests were calculated with Bonferroni correction as post-hoc comparisons. There was a significant difference between rest ($M=1.29$, $SD=0.16$, $r^2=.765$) and self ($M=1.18$, $SD=0.13$, $r^2=.753$), $t(21) = 5.36$, $p = < .001$, 95% CI [0.07, 0.16], as well as between rest ($M=1.29$, $SD=0.16$, $r^2=.765$) and other ($M=1.20$, $SD=0.14$, $r^2=.753$), $t(21) = 5.25$, $p = < .001$, 95% CI [0.05, 0.13]. However, contrary to our initial hypothesis, no significant difference was found between self ($M=1.18$, $SD=0.13$, $r^2=.753$) and other ($M=1.20$, $SD=0.14$, $r^2=.753$), $t(21) = -1.39$, $p = .179$, 95% CI [-0.06, 0.01].

Figure 11

Power spectra by experimental condition

Autocorrelation Window (ACW-50). We then considered continuity in the temporal domain with the autocorrelation function. Since ACW-50 values were considerably non-normal, the Friedman test was employed as a non-parametric alternative to the repeated-measures ANOVA. No differences were observed between rest ($M=11.80$, $SD=4.32$), self ($M=11.64$, $SD=4.32$), and non-self ($M=12.07$, $SD=5.08$) conditions as measured by ACW-50, $\chi^2(2) = 1.091$, $p = .580$.

Autocorrelation Window (ACW-0). However, there was a significant effect of condition seen for ACW-0 values, $F(2,42) = 12.629$, $p < .001$. Mauchly's test did not indicate any violation of sphericity assumptions, $X^2(2) = 5.100$, $p = .078$. Three paired-samples t-tests with Bonferroni correction were then computed for post-hoc comparisons. Our first focus was on whether task-related activity during both self and non-self deviates from the resting state. Significantly longer ACW-0 values were observed in self ($M=169.15$, $SD=58.75$) compared to rest ($M=128.72$, $SD=53.22$), $t(21) = 4.29$, $p < .001$, 95% CI [-60.00, -20.85]. Similar results were obtained for the non-self condition that showed longer ACW-0 values ($M=153.07$, $SD=58.57$) than at rest ($M=128.72$, $SD=53.22$), $t(21) = 2.87$, $p = .009$, 95% CI [-42.02, -6.68].

In a second step, we compared the self- and non-self conditions. We observed a significant difference in average ACW-0 values between self ($M=169.15$, $SD=58.75$) and non-self ($M=153.07$, $SD=58.57$), $t(21) = 2.68$, $p = .014$, 95% CI [3.60, 28.54]. The longer ACW-0 values exhibited in the self condition relative to non-self and rest are visualized in Figure 12. It is relevant to note how the variability in ACF fluctuations decreases noticeably across the three conditions, with the most prominent difference occurring between rest and self. The effect of condition is further illustrated by a topographic analysis shown in Figure 13 and Figure 14.

Figure 12*Autocorrelation plots by experimental condition* *Note.* Vertical lines indicate average ACW-0 values

Figure 13*ACW-0 topoplots comparing rest and task* **Figure 14***ACW-0 topoplots comparing experimental conditions*

Autocorrelation Window (ACW-0) Rest vs Task. Is the ACW deviation from rest stronger in self than non-self? This was addressed by conducting a paired-sample t-test (2-tail) to compare rest-task differences (i.e., rest-self, rest-non-self) in ACW-0. The average difference between rest and self ($M=-40.42$, $SD=44.16$) was significantly greater than the mean difference between rest and non-self ($M=-24.35$, $SD=39.86$), $t(21) = -2.68$, $p = .014$, 95% CI $[-28.54, -3.60]$. This means that the self-narrative induced a significantly longer extension in the ACW-0 during task relative to rest compared to the non-self narrative.

Detrended Fluctuation Analysis. We then probed for scale-freeness in the temporal domain using DFA. A repeated-measures ANOVA demonstrated a significant effect of condition, $F(2, 42) = 12.41$, $p = < .001$, and sphericity assumptions were met, $X^2(2) = 1.73$, $p = .421$. A Bonferroni corrected paired-samples t-test revealed lower DFA values in rest ($M=0.793$, $SD=0.037$) compared to both self ($M=0.812$, $SD=0.039$), $t(21) = -4.30$, $p = < .001$, 95% CI $[-0.03, -0.01]$ and non-self ($M=0.806$, $SD=0.041$), $t(21) = -3.82$, $p = .001$, 95% CI $[-0.02, -0.006]$. However, there was no significant difference between self ($M=0.812$, $SD=0.039$) and non-self ($M=0.806$, $SD=0.041$), $t(21) = 1.513$, $p = .145$, 95% CI $[-0.002, 0.013]$.

Median Frequency. Given the close relationship of ACW to slow frequencies (Honey et al., 2012; Zilio et al., 2021), we also probed the latter using median frequency. Mauchly's test indicated non-sphericity, $X^2(2) = 7.786$, $p = .020$, so a Greenhouse-Geisser correction was applied to the subsequent repeated-measures ANOVA. No significant differences in MF were evinced between rest ($M=7.221$, $SD=2.388$), self ($M= 7.077$, $SD=2.016$), and non-self conditions ($M=7.180$, $SD=2.365$), $F(1.512, 31.758) = .160$, $p = .793$.

Lempel-Ziv Complexity. Sphericity assumptions were violated per Mauchly's test, $X^2(2) = 7.805$, $p = .020$; as such, a Greenhouse-Geisser correction was therefore applied to the degrees

of freedom in the repeated-measures ANOVA. There was no significant difference observed for LZC between rest ($M=0.609$, $SD=0.053$), self ($M=0.615$, $SD=0.052$), and non-self ($M=0.611$, $SD=0.055$), $F(1.512, 31.743) = .401$, $p = .616$.

Alpha Peak Frequency. A Greenhouse-Geisser correction was applied since sphericity could not be assumed after running Mauchly's test, $X^2(2) = 19.69$, $p = < .001$. There were no differences observed between rest ($M=9.62$, $SD=1.26$), self ($M=9.96$, $SD=1.33$), and non-self ($M=9.51$, $SD=1.17$) conditions, $F(1.230, 25.826) = 1.912$, $p = .178$.

Theta Peak Frequency. TPF was considerably non-normal, so a Friedman test was used as a non-parametric alternative to the ANOVA. There was no significant effect of condition on rest ($M=6.29$, $SD=1.17$), self ($M=6.09$, $SD=0.95$), or non-self ($M=6.24$, $SD=1.04$) theta peak frequency values, $\chi^2(2) = 1.727$, $p = .422$.

Band Power. We calculated average band power to complement our MF, APF, and TPF results with a more fine-grained analysis (see Figure 15). In contrast to the aforementioned measures, there was a significant effect of condition revealed by Friedman tests in the delta $\chi^2(2) = 22.909$, $p = < .001$, theta $\chi^2(2) = 25.727$, $p = < .001$, alpha $\chi^2(2) = 13.727$, $p = .001$, beta $\chi^2(2) = 29.545$, $p = < .001$, and gamma bands $\chi^2(2) = 15.636$, $p = < .001$. Post-hoc analysis with Wilcoxon tests revealed significant rest-task differences for each band; however, we did not observe any significant differences between self and non-self after correction for multiple comparisons. The results of our post-hoc analysis are summarized in Table 3 and Table 4 below.

Figure 15*Band power by experimental condition* **Table 3***Band power post-hoc analysis summary*

Comparison	Z	Sig	Sig post-Bonferroni
Delta Rest – Self	-4.010	< .001	√
Delta Rest – Other	-3.750	< .001	√
Delta Self – Other	-1.867	.062	X

Theta Rest – Self	-3.880	< .001	√
Theta Rest – Other	-3.945	< .001	√
Theta Self – Other	-2.127	.033	X

Alpha Rest – Self	-3.523	< .001	√
Alpha Rest – Other	-3.165	.002	√
Alpha Self – Other	-1.607	.108	X

Beta Rest – Self	-4.107	< .001	√
Beta Rest – Other	-3.555	< .001	√

Comparison	Z	Sig	Sig post- Bonferroni
Beta Self – Other	-2.354	.019	X

Gamma Rest – Self	-3.652	< .001	√
Gamma Rest – Other	-2.776	.006	√
Gamma Self – Other	-1.217	.223	X

Table 4*Band power descriptive statistics*

Band, Condition	Mean	Standard Deviation
Delta Rest	1.686	1.109
Delta Self	1.132	.591
Delta Other	1.317	.918

Theta Rest	1.139	1.417
Theta Self	.642	.595
Theta Other	.721	.657

Alpha Rest	1.353	1.617
Alpha Self	.719	.700
Alpha Other	.917	.913

Beta Rest	.259	.156
Beta Self	.189	.125
Beta Other	.211	.139

Gamma Rest	.073	.032
Gamma Self	.057	.021
Gamma Other	.063	.030

Cortical Midline

Normality Assessment. To assess for normality, Shapiro-Wilk tests were performed on data collected from the cortical midline electrodes. The results are summarized in Table 5.

Table 5*Shapiro-Wilk results, cortical midline*

Variable	Test statistic	p-value
PLE Midline - Other	.967	.637
PLE Midline - Rest	.908	.042
PLE Midline - Self	.942	.216

ACW-50 Midline - Other	.891	.020
ACW-50 Midline - Rest	.858	.005
ACW-50 Midline - Self	.802	< .001

ACW-0 Midline - Other	.977	.858
ACW-0 Midline - Rest	.952	.349
ACW-0 Midline - Self	.900	.030

DFA Midline - Other	.975	.816
DFA Midline - Rest	.982	.945
DFA Midline - Self	.973	.782

Power-Law Exponent. Given that previous studies have found an association between cortical midline regions and the self (Northoff & Bermpohl, 2004; Northoff et al., 2006; van den Meer et al., 2010; Qin & Northoff, 2011; Murray et al., 2015; Huang et al., 2016; Wolff et al., 2019), we decided to target the midline electrodes for further analysis. There was a significant effect of condition observed in this subset, $F(2, 42) = 12.427, p = < .001$. Assumptions of sphericity were met, $X^2(2) = .450, p = .798$. A post-hoc analysis demonstrated larger PLE values at rest ($M=1.34, SD=0.16, r^2=.769$) than in self ($M=1.24, SD=0.14, r^2=.755$), $t(21) = 4.633, p = < .001$, 95% CI [0.055, 0.145], or non-self ($M=1.29, SD=0.15, r^2=.758$), $t(21) = 3.010, p = .007$, 95% CI [0.018, 0.098]. A small difference was exhibited between self ($M=1.24, SD=0.14, r^2=.755$) and non-self ($M=1.29, SD=0.15, r^2=.758$), $t(21) = -2.157, p = .043$, 95% CI [-0.083, -0.002]. However, this difference did not retain statistical significance after the Bonferroni correction.

Autocorrelation Window (ACW-50). A Friedman test was used to compare ACW-50 values in rest, self, and non-self conditions because normality assumptions were violated per the Shapiro-Wilk test. There was no effect of condition on ACW-50 scores in the midline electrode subset, $\chi^2(2) = 5.167, p = .076$.

Autocorrelation Window (ACW-0). Like the whole-brain analysis, there was a significant effect of condition on ACW-0 values, $F(2, 42) = 12.511, p = < .001$. The sphericity assumption was met, $X^2(2) = 1.610, p = .447$. Post-hoc comparisons showed longer ACWs in self ($M=170.835, SD=56.172$) than during rest ($M=132.616, SD=55.382$), $t(21) = -4.441, p = < .001$, 95% CI $[-56.114, -20.324]$. Non-self ($M=152.730, SD=57.536$) also exhibited longer ACWs than rest ($M=132.616, SD=55.382$), $t(21) = -2.724, p = .013$, 95% CI $[-35.469, -4.759]$. Finally, longer ACWs were observed in self ($M=170.835, SD=56.172$) than in non-self ($M=152.730, SD=57.536$), $t(21) = 2.649, p = .015$, 95% CI $[3.889, 32.321]$.

Detrended Fluctuation Analysis. An effect of condition on DFA values was observed over the midline electrodes, $F(2, 42) = 17.221, p = < .001$. Mauchly's test did not indicate any violations of sphericity, $X^2(2) = 1.794, p = .408$. Post-hoc analysis revealed larger DFA exponents in self ($M=0.817, SD=0.038$) compared to rest ($M=0.799, SD=0.036$), $t(21) = -4.908, p = < .001$, 95% CI $[-0.026, -0.010]$. Average DFA was similarly larger in non-self ($M=0.813, SD=0.039$) compared to rest ($M=0.799, SD=0.036$), $t(21) = -5.094, p = < .001$, 95% CI $[-0.020, -0.009]$. There was no significant difference between self ($M=0.817, SD=0.038$) and non-self ($M=0.813, SD=0.039$) DFA values, $t(21) = 1.091, p = .288$, 95% CI $[-0.003, 0.010]$.

Correlational Analysis

Brain and Behavior

Exploratory spearman correlations were calculated to probe the relationship between neural and behavioral timeseries. The statistically significant results are highlighted in Table 6, below.

Table 6

Spearman correlations of brain and behavior.

Variables	p-value	Rho
ACW-0 EEG self - DFA behavior other	.016	.508

TPF EEG other - DFA behavior other	.038	-.446
TPF EEG self - DFA behavior other	.019	-.495

DFA EEG self - DFA behavior other	.010	.535

PLE midline EEG self – ACW-0 behavior Self	.036	-.450
PLE midline EEG self – ACW-0 behavior Other	.043	-.435

ACW-50 midline EEG rest - DFA Behavior Other	.006	.563
ACW-0 midline EEG other - DFA Behavior Other	.043	.435
ACW-0 midline EEG self - DFA Behavior Other	.020	.494

DFA midline EEG other - DFA Behavior Other	.037	.446
DFA midline EEG rest - DFA Behavior Other	.019	.496
DFA midline EEG self - DFA Behavior Other	.007	.561

Exploratory Correlation of Neuronal Values and Psychological Scales

An exploratory correlational analysis probed the relationship between EEG data and psychological scales using Spearman rank-order correlations. The significant results are summarized in Table 7. Notably, all measures exhibited some degree of correlation with psychological scale data.

Table 7*Spearman correlations of neuronal values and psychological scales*

Variables	p-value	Rho
ACW-0 Neuronal Other - NYCQ Friend	.034	.455
ACW-0 Neuronal Rest – NYCQ Word	.047	.428
ACW-0 Neuronal Self –NYCQ Friend	.005	.576
ACW-0 Neuronal Self – ZTP Past Positive	.017	-.503
ACW-50 Neuronal Other – PNI Total	.011	-.532
ACW-50 Neuronal Other – PNI Narcissistic Grandiosity	< .001	-.670
ACW-50 Neuronal Other – ZTP Past Positive	.016	-.509
ACW-50 Neuronal Rest – PNI Total	.006	-.566
ACW-50 Neuronal Rest – PNI Narcissistic Grandiosity	< .001	-.665
ACW-50 Neuronal Rest – ZTP Past Positive	.012	-.524
ACW-50 Neuronal Self – NYCQ Future	.037	-.446
ACW-50 Neuronal Self – NYCQ Friend	.015	.513

PLE Neuronal Other – RSES Total	.014	.518
PLE Neuronal Other – SCC Total	.008	.552
PLE Neuronal Other – CTQ Total	.019	-.497
PLE Neuronal Self – ISES Total	.027	-.470
PLE Neuronal Self – RSES Total	.009	.545
PLE Neuronal Self – SCC Total	.023	.482
PLE Neuronal Self – NYCQ Future	.031	-.460
PLE Neuronal Self – NYCQ Vague	.027	-.472
PLE Neuronal Self – ZTP Past Negative	.016	-.509

MF Neuronal Other – PNI Narcissistic Grandiosity	.002	.627
MF Neuronal Other – ZTP Past Positive	.012	.526
MF Neuronal Rest – PNI Narcissistic Grandiosity	.013	.522
MF Neuronal Rest – ZTP Past Positive	.026	.473
MF Neuronal Self – NYCQ Future	.030	.464
MF Neuronal Self – NYCQ Friend	.030	-.463
MF Neuronal Self – ZTP Past Positive	.040	.440

LZC Neuronal Other – SCC Total	.046	-.429
LZC Neuronal Other – PNI Total	.044	.434

APF Neuronal Other – PNI Narcissistic Grandiosity	.026	.475
APF Neuronal Rest – PNI Narcissistic Grandiosity	.037	.448

TPF Neuronal Other – CTQ Total	.007	-.560
TPF Neuronal Other – ZTP Past Positive	.024	.479
TPF Neuronal Rest – ZTP Past Positive	.005	.581

Variables	p-value	Rho
TPF Neuronal Rest – ZTP Future	.046	.430
TPF Neuronal Self – ZTP Past Positive	.018	.500

DFA Neuronal Other – PNI Total	.004	-.583
DFA Neuronal Other – PNI Narcissistic Grandiosity	.001	-.645
DFA Neuronal Rest – PNI Total	.020	-.493
DFA Neuronal Rest – PNI Narcissistic Grandiosity	.016	-.508
DFA Neuronal Rest – NYCQ Friend	.040	.441
DFA Neuronal Self – PNI Total	.037	-.447
DFA Neuronal Self – PNI Narcissistic Grandiosity	.029	-.466
DFA Neuronal Self – NYCQ Friend	.010	.535
DFA Neuronal Self – ZTP Past Positive	.022	-.485

Exploratory Correlation of Behavior and Scales

Spearman correlations were performed between behavioral data and psychological scales as a second exploratory analysis. The significant combinations are presented in Table 8.

Table 8

Spearman correlations of behavioral timeseries and scales.

Variables	p-value	Rho
PLE Behavior Other – NYCQ Positive	.028	.431
PLE Behavior Other – NYCQ Friend	.036	.413

LZC Behavior Self – CTQ Total	.031	.433

DFA Behavior Self – ZTP PH	.049	-.390
DFA Behavior Other – NYCQ Positive	.039	-.406

ACW-50 Behavior Other – SCS Private	.019	-.457
ACW-50 Behavior Other – ZTP PP	.045	-.397

Discussion

The current investigation probed the relationship between brain and behavior for a shared feature or ‘common currency.’ We hypothesized that temporal integration would serve as this

bridge. To test this, we first applied scale-free measures to a behavioral timeseries and found significantly higher PLE and ACW-50 values in the self narrative compared to the non-self narrative. We then applied the same procedures to the neuronal timeseries and computed Spearman's rank-order correlations to determine the degree of connection between the modalities. We expected results from the neuronal and behavioral timeseries to mirror each other and exhibit strong and positive cross-modality correlations between respective measures (e.g., PLE behavior correlating with PLE neuronal). The predicted 1:1 correspondence did not materialize, and the correlational analysis between brain and behavior did not yield conclusive results. However, our hypothesis was partially supported as self-specificity was observed for neuronal ACW-0. Indices of temporal continuity therefore exhibited larger values during self-compared to non-self-referential processing in both EEG and behavior. It is noteworthy that the neuronal measure reflects continuity in the temporal domain whereas the behavioral measure represents temporal continuity in the temporal and frequency domains. While the reasons for this time-frequency discrepancy remain unclear, we will provide a tentative explanation and situate these findings within the context of relevant literature.

Neuronal Findings

Rest-Task Differences

The majority of our scale-free measures (i.e., PLE, DFA, ACW-0) exhibited a significant rest-task difference whereas no significant rest-task differences were evidenced in the non-fractal measures (i.e., LZC, MF, TPF, APF). This manifested in the frequency domain as a suppression of LRTC during task conditions relative to rest; however, in the temporal domain, there was a marked increase in LRTC during task-evoked activity.

These observations can be considered in the context of previous studies exploring rest-task differences in EEG or fMRI. For instance, the default mode interference hypothesis (Sonuga-Barke & Castellanos, 2007) predicts that within the DMN, low frequency oscillatory fluctuations will be reduced in task states relative to rest. This theory finds support in an EEG study by Helps et al. (2010) which showed attenuated low frequency activity after participants transitioned from rest to task. This is indicative of task-evoked LRTC attenuation due to the close association between LRTC and slow-frequency activity (Linkenkaer-Hansen et al., 2001). In fMRI, Kasagi et al. (2017) found that PLE in the medial prefrontal cortex decreased significantly in task-evoked activity compared to rest. Since this reduction was associated with improved reaction times in a behavioral task, the researchers suggested that task-related LRTC suppression may be associated with efficient information processing. The suppression of LRTC in task states is further supported in fMRI by Churchill et al. (2016) and Ciuciu et al. (2012). The former found that fractal scaling decreased in response to task novelty, task difficulty, and age. Ciuciu et al. (2012) noted a general task-related suppression of LRTC in functional networks. Finally, an EEG study by Irrmicher et al. (2018) demonstrated a reduction in LRTC during an attention task compared to rest. Like Kasagi et al. (2017), Irrmicher et al. (2018) found that LRTC suppression correlated with better task performance.

These studies support the assumption that LRTC, indexed by either PLE or DFA, decreases in response to cognitive load. However, there is further corroborating evidence from studies exploring rest-task differences using the autocorrelation function. Golesorkhi et al. (2021), for instance, found a decrease in ACW across working memory, linguistic processing, and motor tasks compared to rest. Similar results were obtained in EEG where shorter ACWs

were demonstrated during task compared to rest for healthy but not schizophrenic subjects in an enfacement-illusion paradigm (Northoff et al., 2021).

Overall, this literature provides a framework for the rest-task findings of the current investigation. Contrary to the multitude of studies exhibiting a decrease in fractal scaling and LRTC between rest and task, our own results differ between temporal and frequency domains. While the reasons for this discrepancy are unclear, it is relevant to consider that our study is designed to assess self- vs non-self-referential processing, whereas the task states in the aforementioned studies had an entirely different focus. There was a significantly larger divergence from rest in the self-condition compared to non-self implying that the self-narrative induced an extension in the ACW-0 during task relative to rest. This may partially explain the discrepancy between our results and those of others. The continuous nature of our task may also be a relevant factor.

Autocorrelation Window

The sole empirical measure to exhibit self-specificity (i.e., an effect of task condition) in the neuronal data was the ACW-0. Interestingly, ACW-50 could not discriminate between self and non-self with its shorter window sizes; the intrinsically larger timescales of ACW-0 were necessary for this purpose. We observed significantly longer ACWs during self-referential processing compared to both non-self-referential processing and rest. Since longer timescales have previously been associated with the self in psychological scales or behavioral tasks (Wolff et al., 2019; Kolvoort et al., 2020), it is plausible that only the ACW-0 would possess the necessary resolution to capture the full range of activity.

However, this window extension was not the result of increased power in slow frequency brain activity that would be expected mathematically based on the Blackman-Tukey approach

(Blackman & Tukey, 1958), a derivation of the Wiener-Khinchin theorem (Wiener, 1930; Khinchin, 1934). The approach states that the power spectral density (PSD) of a signal is equivalent to the Fourier transformation of its autocorrelation function. While Blackman-Tukey only postulates a theoretical relationship between ACW and PSD, there are empirical instantiations of their approach that suggest a key role for slow-frequency activity. For instance, an ECoG study by Honey et al. (2012) demonstrated that the amplitude of slow frequency fluctuations correlates positively with ACW during a 30 sec pre-stimulus period, and while viewing intact or scrambled video segments. A similar finding was observed in EEG by Zilio et al. (2021) who noted that prolonged ACWs in non-conscious patients (i.e., sleep, anesthesia, and unresponsive wakefulness syndrome) were accompanied by shifts towards slower frequencies. On the contrary, we noted a large power reduction in most frequency bands during task-evoked activity, most dramatically in delta, theta, and alpha. The power was also lowest while participants listened to their own autobiographical narrative. A different generative mechanism other than slow-frequency fluctuations must therefore be driving the increased ACWs.

Whole Brain and Cortical Midline

We targeted the midline electrodes since previous studies have reported a connection between cortical midline regions and the self (Northoff & Bermpohl, 2004; Northoff et al., 2006; van der Meer et al., 2010; Qin & Northoff, 2011; Murray et al., 2015; Huang et al., 2016; Wolff et al., 2019). A more pronounced effect of task condition was therefore expected here. Surprisingly, midline electrodes exhibited nearly the same pattern of results as the whole-brain analysis; PLE was still lower in task compared to rest while ACW-0 and DFA remained greater during task. As with the whole brain approach, midline ACW-0 was the only measure to exhibit self-specificity (i.e., the ability to distinguish between self and non-self). The difference between

self and non-self PLE was slightly more pronounced in midline electrodes compared to the whole-brain, with larger PLE values observed in the non-self condition. However, the statistical significance was not supported after Bonferroni correction. Thus, the current findings do not corroborate previous studies linking midline regions and the self, although a source-space analysis (e.g., eLORETA) could yield more corroboratively supportive results.

Behavioral Findings

The raw cursor distance from center was larger for self than non-self indicating that participants evaluated themselves more negatively than the stranger. An alternative interpretation may be that subjects felt more inclined to explore their peri-personal space while listening to their own narrative, resulting in broader, more expansive movements. However, a detailed comparison between these competing explanations is beyond the scope of the current investigation whose primary objective is to consider the behavioral data in the context of fractal dynamics and temporal continuity.

The cursor movements displayed a meaningful temporospatial structure that manifested as scale-freeness of the relationship between power and frequency with temporal nestedness and LRTC. This in itself is an interesting finding, and corroborates a previous cursor-paradigm experiment by Wong et al (2014) which also observed LRTC in the cursor movements over time. Most relevant to the present investigation, however, was that PLE and ACW-50 displayed an effect of condition with significantly higher values obtained in self than non-self for both. Surprisingly, and in contrast to our EEG findings, the ACW-50 but not ACW-0 exhibited self-specificity. The shorter timescales of the behavioral signal were therefore most relevant for discriminating self and non-self, despite recent findings associating longer timescales with the self (Wolff et al., 2019; Kolvoort et al., 2020). The paucity of empirical data linking LRTC and

behavior poses an interpretive challenge. Ultimately, however, we believe the behavioral results are best interpreted within the context of a common currency which is elucidated in the following section.

Relationship Between Brain and Behavior

Common Currency

We probed the relationship between brain and behavior to determine whether temporal continuity serves as a bridge. It was assumed that we would find a 1:1 correspondence between respective scale-free measures across behavioral and neuronal modalities. This hypothesis was, however, only partially supported. Greater LRTC was demonstrated in response to the self-narrative for neuronal and behavioral modalities, although not between identical measures. In the brain, we found that ACW-0 was longer in the self-condition; on the behavioral level, PLE and ACW-50 exhibited larger values. Temporal continuity was therefore relevant neurally in the temporal domain and behaviorally in both the temporal and frequency domains.

The most direct relationship between brain and behavior was observed in the temporal domain with autocorrelation. Notably, derivatives of the ACF showed greater LRTC during self-referential processing compared to non-self-referential processing in their respective modalities. However, it remains unclear why longer timescales (i.e., ACW-0) discriminated self and non-self in EEG whereas shorter timescales (ACW-50) had higher relevance in the cursor data. Future work in this area may offer conclusive outcomes, but the novelty of our study currently precludes direct comparisons. There are a limited number of studies that compare neural and behavioral LRTC (Palva et al., 2013; Smit et al., 2013), although none that consider the self to our knowledge. Broadly speaking, and despite the different timescales associated with ACW-50 and

ACW-0, this finding can be viewed as support for a common feature shared between brain and behavior.

The association between neuronal ACW-0 and behavioral PLE is less straightforward. A direct relationship would require that we assume some form of time-frequency transformation between brain and behavior. While possible, this claim would require more in-depth research as currently, there is a paucity of supporting empirical evidence. An indirect relationship is another consideration which would imply mediation by a third variable such as the ACW-50. This is, admittedly, similarly hypothetical.

Our correlational analysis did not offer improved clarification. There was a connection between ACW-0 and PLE across brain and behavior; however, the p-values were not particularly convincing, and the correlation was observed between neuronal PLE and behavioral ACW-0. This empirical outcome is in contrast to our expected results given that neither demonstrated any effect of task condition. Additionally, there was no significant correlation between neuronal ACW-0 and behavioral ACW-50, and such a correlation would be expected for any variables comprising a common currency. These inconsistencies are in contradistinction to Palva et al. (2013) who, similar to our approach, analyzed LRTC across M/EEG and behavior. Palva et al. (2013) found that DFA exponents in the brain correlated positively with those in an event-based audiovisual stimulus detection task. Regardless, we tentatively view the balance of evidence as support for the common currency hypothesis, but our results indicate the need for a more nuanced operationalization.

Input Processing and Outputs

Arguably, this refinement process can begin by taking neuronal input processing literature into consideration. This interpretive lens is necessary since the paradigm was designed

such that participants were exposed to continuous inputs over eight-minutes in each study condition. Participants received these inputs and then reported their evaluative determination by moving the cursor relative to the center of the screen. It therefore plausible that ACW-0 reflects external stimulus processing whereas PLE and ACW-50 describe properties of the output. This interpretation enjoys strong support neuronally, although our view of behavioral LRTC as an output is speculative since there are a limited number of behaviorally relevant studies.

Neuronally, the autocorrelation function is one method of operationalizing intrinsic neural timescales (INTs; Murray et al., 2014). These INTs are known to form a complex temporal hierarchy along a gradient from unimodal to transmodal brain regions (Stephens et al., 2013; Watanabe et al., 2019; Gao et al., 2020; Ito et al., 2020; Raut et al., 2020; Golesorkhi et al., 2021; Demirtas et al., 2019). Unimodal regions including the early auditory cortex process the shortest timescales of an external stimulus such as the combination of individual letters into words. In contrast, higher order transmodal regions like the default mode network (DMN) preferentially parse longer segments such as entire paragraphs (Yeshurun et al. 2021; Stephens et al., 2013; Honey et al., 2012; Simony et al., 2015; Chen et al., 2017).

Furthermore, the brain's spontaneous activity exhibits an analogous temporal structure as shorter ACWs tend to be observed in unimodal areas and longer ACWs are obtained from higher-order transmodal regions such as the DMN (Chaudhuri et al., 2015, 2019; Murray et al., 2014; Ito et al., 2020; Honey et al., 2012; Golesorkhi et al., 2021, 2020; Raut et al., 2020; Wengler et al., 2020). Task studies also show input segmenting as the window lengths in the brain match those of the input (Hasson et al., 2015; Chen et al., 2015; Regev et al., 2019; Nguyen et al., 2019; Ventriglia, 2014; Deli et al., 2017).

This latter point is particularly relevant in the context of self-referential processing since, conceptually speaking, the self can be seen to match its own timescales with the correspondingly longer windows of the continuous input stream. In more concrete terms, we may prefer to say that the timescales associated with the neural circuitry underpinning our sense of self are matched to those of the stimulus. In either case, interindividual differences in INTs could presumably affect the degree of matching between self and stimulus and therefore account for the subjective character of input processing.

Our results corroborate findings from Zilio et al. (2021) who, like others, suggest that INTs mediate input processing and can be indexed by the ACW. They compared resting-state ACW values in two groups of participants: those with impairments receiving sensory input (i.e., anesthesia, sleep, and disorders of consciousness) and those with motor deficits (i.e., locked-in syndrome [LIS] and amyotrophic lateral sclerosis [ALS]). Participants in the former group exhibited abnormally extended ACW values whereas the latter displayed typical window sizes. This shift to longer windows in unconscious participants indicates that their shorter timescales were both absent and necessary for processing external stimuli. The fact that LIS or ALS subjects did not present with any changes to their ACW led the authors to conclude that ACW is specifically related to sensory input processing. This is pertinent to our discussion since we similarly showed that neuronal ACW-0 is responsive to external inputs over an extended period.

The relationship between LRTC and outward behavior has received significantly less attention than the study of sensory input processing. Regardless, there is some evidence connecting PLE and other measures of temporal continuity to task data. Smit et al. (2013), for instance, found that timing errors in a finger-tapping task exhibited fractal properties indexed by DFA and PLE. This was further supported by Palva et al. (2013) who demonstrated LRTC in

audiovisual stimulus detection, also measured with DFA. Finally, Wong et al. (2014) found that when mouse-cursor movements in response to an autobiographical narrative were visualized in the spectral domain using a double-log plot, the data were linear and followed a power-law distribution. Our own study adds to this behavioral LRTC literature and suggests, albeit tentatively, that LRTC is implicated in sensory input processing yet also describes properties of behavioral outputs. While the precise mechanisms by which the former shapes the latter remain undefined, the common currency hypothesis offers an interpretive lens and framework for future research.

Strengths, Limitations, Future Research

The current investigation is unique in its approach of applying identical empirical measures to concurrent, continuous behavioral and neuronal timeseries. However, there are some important limitations that need to be addressed. First, our sample size was too small to draw meaningful conclusions about our psychological scales and their relationships with other data; while interesting, these results may serve to motivate and inform future studies with a larger pool of subjects. Second, we did not analyze the temporal features of the self and non-self narratives themselves. Characteristics of these narratives could be quantified in order to ensure that conditional effects are not the result of objective differences in the recordings. Alternatively, subjects could be exposed to their own narrative spoken by a stranger in one condition to control for qualitative differences in narrative content. Finally, we only conducted a sensor-space analysis which precludes reliable statements about the importance of spatial topography such as the cortical midline regions. Future research could extend the study into source-space with eLORETA or a modality with higher spatial resolution such as fMRI. We consider this to be a

necessary step as the intrinsic neural timescales relevant for input processing have an inherent spatial dimension.

Conclusion

The current investigation probed the relationship between brain and behavior for a bridging mechanism or common currency. Specifically, our hypothesis was that temporal continuity on the neuronal level would manifest in participant behavior. This hypothesis was partially supported. Indices of temporal integration did exhibit task-evoked self-specificity in both EEG and behavior data; however, 1:1 correspondence between the two modalities with respect to the measure of temporal continuity was not demonstrated. We believe, based on our results, that a more granular operationalization of the common currency theory could warrant further exploration.

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Appendix A

Demographic Health Questionnaire

1. Have you ever been diagnosed with a mental illness or condition (ex. Depression, anxiety, posttraumatic stress disorder, etc.)? _____
If yes, which illness and when? _____
2. Have you ever been diagnosed with a neurological condition (ex. Epilepsy, stroke, dementia, etc.)? _____
If yes, which condition and when? _____
3. Have you ever had a head injury that was treated by a doctor? _____
4. Have you ever been knocked unconscious for more than 5 minutes? _____
5. In the past 3 months have you used alcohol or drugs in a way that caused you to take risks, neglected your responsibilities, or caused problems in your relationships with friends or family? _____
6. Have you ever used alcohol or drugs in a way that you knew was hurting you, where you needed more of it to get the same feeling, or used it to make yourself feel better physically or mentally? _____
7. Have you ever been treated with chemotherapy, radiation therapy to your brain or electroconvulsive therapy (ECT)? _____
8. Are you currently taking any medication by a doctor?
If yes, which medication? _____
9. Are you below the age of 18? _____
10. Do you need glasses to read? _____
If so, do you have them with you today? _____
11. In the last 7 days, have you smoked cigarettes on a regular basis? _____
12. In the last 7 days, have you smoked cigarettes or ingested marijuana? _____
13. In the last 7 days, have you taken any other medication not listed above (ex. Advil, Tylenol, Tylenol-3, multivitamin, etc)? _____
If yes, which medication? _____
14. What is your approximate height? _____
15. What is your approximate weight? _____

16. Sex _____
17. Highest education _____
18. When did you last eat (in hours)? _____

Appendix B

Informed Consent Form for Study Participants

Title of Protocol: "The Fractal dynamics of the Self"

Principal Investigators: David Smith

Participant Name: _____

I, _____, have read the preceding information and have had a chance to ask questions to help me understand what my participation will involve. My signature below indicates that the study and related procedures have been explained to me and that I freely give my consent to participate in the study unless I decide otherwise. I will receive a signed copy of this consent form.

Participant (Print Name)	Signature	Date

Person Obtaining Consent (Print Name)	Signature	Date

Investigator Statement

I certify that I have explained the research study to the above individual, including the purpose, the procedures, the possible risks and potential benefits associated with participation in this research study. Any questions raised have been answered to the individual's satisfaction. I believe that the participant fully understands my explanations and has freely given informed consent.

Investigator (Print Name)	Signature	Date