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Individual differences in brain signal complexity and their relationship with creativity

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Contents

Abstract

The brain is a nested network of coupled dynamical systems of interacting neuronal populations that give rise to complexity. Neural complexity provides a measure for the amount of information that is integrated within a neural system. Neural complexity can be assessed by computing brain signal complexity (BSC). The BSC in resting state has been shown to be associated with various cognitive functions, particularly with creativity. Multi-Scale Entropy (MSE) is an index of BSC that examines the complexity of spatiotemporal patterns underlying certain cognitive processes. This dissertation assesses the utility of MSE for measuring BSC associated with cognitive abilities, specifically with creativity. The overarching aim was to assess whether creativity can be parameterized in terms of BSC as measured by entropy in brain signals obtained via the scalp-recorded electroencephalogram (EEG). First, the dissertation aimed to investigate MSE in different brain states (i.e., resting versus task states) from an individual differences perspective and determine the reliability of MSE measures across individuals using EEG (**Study 1**). Findings revealed that individual differences in MSE are stable and can be measured reliably, qualifying MSE to be a useful trait marker of BSC across individuals. Second, the dissertation aimed to assess neural mechanisms underlying verbal creativity in the EEG signals (**Study 2**). Findings showed that MSE was modulated by originality during verbal production, indicating that BSC is a potential neural marker of verbal creativity. Finally, the dissertation explored the relationship between MSE and more nuanced facets of creativity (i.e., fluency, originality; fluid and crystallized intelligence, and inhibition; **Study 3**). Findings in this study indicated that individuals with higher BSC in creative and inhibitory neural states are better at reasoning and at producing fluent and original associations. Furthermore, MSE is not only a highly specific neural marker of verbal creativity, but of inhibition and intelligence as well. Taken together, the dissertation provides valuable insights for designing future studies using MSE to assess neural complexity and its relationship with creativity, intelligence, and inhibition. Furthermore, the work demonstrates that complex, high level cognitive functions which can be difficult to capture using traditional EEG measures, can be understood using cutting-edge tools for measuring BSC.

Zusammenfassung

Das Gehirn ist ein komplexes Netzwerk aus gekoppelten, dynamischen Systemen interagierender Neuronenpopulationen, welche neuronale Komplexität erzeugen. Die neuronale Komplexität ist ein Maß für die Menge an Informationen, die in einem neuronalen System integriert ist. Sie kann anhand der Gehirnsignalkomplexität (brain signal complexity, BSC) gemessen werden. Studien konnten zeigen, dass die BSC im Ruhezustand mit verschiedenen kognitiven Funktionen in Verbindung steht, insbesondere mit der Kreativität. Die Multi-Skalen-Entropie (MSE) ist ein Index der BSC, der die Komplexität räumlicher und zeitlicher Signalmuster untersucht, welche kognitiven Prozessen zugrunde liegen. In dieser Dissertation wird die Nützlichkeit der MSE zur Messung der BSC im Zusammenhang mit kognitiven Fähigkeiten untersucht, insbesondere mit Kreativität. Das übergeordnete Ziel der Arbeit ist es, zu beurteilen, ob die kreative Ideengenerierung vom Ausmaß der im Elektroenzephalogramm (EEG) mittels MSE gemessenen neuronalen Komplexität vorhergesagt wird. Erstens zielte die Dissertation darauf ab, individuelle Unterschiede in der MSE in verschiedenen Hirnzuständen (d. h. Ruhe- und Aufgabenzustand) mittels EEG zu untersuchen und die Reliabilität der MSE-Messungen bei verschiedenen Personen zu bestimmen (**Studie 1**). Die Ergebnisse zeigten, dass die MSE sensitiv zwischen verschiedenen Hirnzuständen unterscheiden kann und als reliables Merkmalsmaß für Personen genutzt werden kann. Zweitens zielte die Dissertation darauf ab, die neuronalen Mechanismen, die der verbalen Kreativität zugrunde liegen, mittels EEG zu untersuchen (**Studie 2**). Die Ergebnisse zeigen, dass die MSE durch Originalität während der verbalen Produktion moduliert wurde, was darauf hindeutet, dass die BSC ein potentieller neuronaler Marker für verbale Kreativität ist. Schließlich untersuchte die Dissertation die Beziehung zwischen MSE und verschiedenen Facetten der Kreativität (Ideenflüssigkeit, Originalität, fluide und kristalline Intelligenz sowie Inhibition; **Studie 3**). Die Ergebnisse dieser Studie deuten darauf hin, dass Personen mit höherer MSE in kreativen und hemmenden neuronalen Zuständen stärker ausgeprägte Fähigkeiten im logischen Denken sowie in der Produktion flüssiger und origineller verbaler Assoziationen zeigen. Darüber hinaus ist die MSE nicht nur ein hochspezifischer neuronaler Marker für verbale Kreativität, sondern auch für Inhibition und Intelligenz. Insgesamt liefert die Dissertation wertvolle Erkenntnisse für zukünftige Studien, die MSE zur Beurteilung neuronaler Komplexität und ihrer

Beziehung zu Kreativität, Intelligenz und Inhibition verwenden. Schließlich zeigt die Arbeit, dass komplexe kognitive Fähigkeiten höherer Ordnung, die mit traditionellen EEG-Methoden nur schwer zu erfassen sind, mit modernsten Techniken zur Messung der BSC untersucht werden können.

Figures

Tables

Abbreviations

Ag/AgCl	Silver/ Silver chloride
AUC	Area under the curve
BA 10	Brodmann area 10
BSC	Brain signal complexity
CCN	Cognitive control network
CFI	Comparative fit index
CHC	Cattell-Horn-Carroll model
df	Degrees of freedom
DMN	Default mode network
DT	Divergent thinking
ECN	Executive control network
EEG	Electroencephalography
ERP	Event Related Potential
FIR	Finite impulse response
fMRI	Functional Magnetic Resonance Imaging
g	General intelligence
gc	Crystallized intelligence
gf	Fluid intelligence
glr	Long-term retrieval ability
HT	Honing theory of creativity
ICC	intraclass correlation
ICA	Independent Component Analysis
IIR	Infinite impulse response
Lavaan	Latent variable analyses
LDSM	Latent difference score modeling
m	Pattern length
MATLAB	MATrix LABoratory

PFC	pre-frontal cortex
r	Threshold
RMSEA	Root Mean Square Error of Approximation
RSCE	Resting state closed eyes
RSOE	Resting state open eyes
SA	Similar attributes
SampEn	Sample entropy
SASICA	SemiAutomatic Selection of Independent Components for Artifact correction
SD	Standard Deviation
SEM	Structural equation modeling
SN	Salience network
SOI	Guilford's Structure of Intellect
SRMR	Standardized Root Mean-square Square Residual
TCs	Task conditions
VKT	Verbaler Kreativitäts-Test

"Whereas creativity involves traits that make a person creative, creating calls upon many resources not intrinsically creative."

David N. Perkins (1981, p. 275)

1 General introduction

1.1 Creativity and its relevance for research

The current dissertation focuses on the cornerstone characteristic of the human mind: Creativity, a complex ability essential to human and societal development (Gabora & Kaufman, 2010). The etymology of creativity lies in the Latin verb *creare*, meaning to make or produce something. The modern definition of creativity is to generate an idea or product which is a combination of novelty (or originality) and utility (or effectiveness, or value; Runco & Jaeger, 2012). Traditionally, creativity was considered as the province of artists such as musicians, painters or writers (Abraham, 2018). However, in the complex work environments of the present day, creativity has become a vital cognitive ability in many aspects of life. For example, creative thinking is important for occupational success (Plucker & Renzulli, 1999; Torrance, 1988) and plays an important role in planning, problem solving, and story-telling giving rise to science, art, and technology (Gabora, 2017).

The investigation of the neural bases of creativity has been of great interest for researchers. Creativity is associated with activity patterns in widespread neural networks (Fink & Benedek, 2016). However, creativity is a complex cognitive construct (Gabora, 2017) and the investigation of its neural correlates is not straightforward. Specifically, the field still lacks an understanding of the neural correlates of creativity in the framework of nonlinear dynamical systems (Stam, 2005), one of the most modern frameworks for describing human brain functions. Thus, there is a need for interdisciplinary research which combines modern psychometrics and computational modeling of brain signals that are led by well-grounded theories on human cognition to study brain-behavior relationships of creativity. **Therefore, the current dissertation is an effort to investigate and understand creativity at the behavioral and neural level in the framework of dynamical systems theory.** For this purpose, the dissertation presents three studies which shed light on the complex construct of creativity at the behavioral and neural levels and also investigate the relationship between creativity and associated constructs such as intelligence and cognitive control. Before presenting the studies in detail, the following sections provide a general overview

of how creativity is typically measured and defined, the relationship between creativity, intelligence, and cognitive control, and how creativity is conceived as a complex construct that may be optimally measured using novel methods for assessing complex neural activity.

1.2 Measurement and magnitude of creativity

Divergent thinking (DT) tasks are the most widely used measures in creativity research. The popularity of DT tasks increased after Guilford's Structure of Intellect (SOI; Guilford, 1967) was published which conceived creativity as a subset of intelligence and conceptualized it as a normally distributed trait. Specifically, the SOI model describes idea production as **convergent** or **divergent**. **Convergent production of ideas requires the production of one single correct answer to a highly structured task or problem, whereas divergent production of ideas requires the production of a variety of responses to a relatively unstructured task or problem** (Runco, 2010). Therefore, convergent thinking and DT are considered as mental bases for intelligence and creativity, respectively. DT tasks have been validated as predictors of everyday creativity (Runco & Acar, 2012). Therefore, creativity is commonly assessed via DT tasks, capturing the facets of *fluency*, *flexibility*, and *originality* (Carroll, 1993). **Fluency** is a quantitative facet that refers to the number of ideas produced. **Flexibility** represents category shifts when producing multiple ideas. **Originality** refers to the uniqueness of the generated ideas.

After the initial publication of the SOI model, many theorists also started to frame creativity as a subset of intelligence. For instance, creativity was implemented into the Cattell-Horn-Carroll model (CHC model; Flangan & Dixon, 2014; McGrew, 2009), one of the most widely used structural models of human cognitive abilities. This theory emerged from the fluid (gf) and crystallized intelligence (gf–gc) theory (Horn & Cattell, 1966) and Carroll's (1993) three-stratum theory. The hierarchical framework of the CHC model consists of three strata in which general intelligence (g) lies in the top layer (Stratum III) and broad cognitive abilities are included in the second layer (Stratum II). For example, gf, gc, and long-term retrieval (glr) belong to Stratum II. gf is commonly defined as the ability to think deductively or to solve problems in unfamiliar domains using abstract reasoning methods. In contrast, gc is defined as the ability to solve problems in familiar domains using knowledge acquired through education, training, or

acculturation. glr is the ability to store information in and fluently retrieve it from long-term memory at a later occasion (e.g., concepts, ideas, items, names; Carroll, 1993; Cattell, 1963). Abilities relevant for creativity such as originality are integrated into the bottom layer (Stratum I) subsumed under the glr ability. Originality is defined as the ability to rapidly produce unusual, original, clever, divergent, or uncommon responses (expressions, interpretations) to a given topic, situation, or task.

However, before the assessment of creativity, it is critical to adequately consider the magnitude of creativity. Based on the definition and assessment of creativity, its' magnitude can take four forms (Abraham, 2018; Kaufman & Beghetto, 2009): 1) *Mini-c* which reflects personal meaningful interpretations of the experiences, actions, and events, and developmental nature of creativity, 2) *Little-C* refers to creative engagement beyond the intrapersonal space, 3) *Pro-C* refers to higher level of creativity where significant creative achievements are evidenced, and 4) *Big-C* represents creativity on a monumental lasting scale which is professionally and publicly recognizable performance. Therefore, the creative work of artists, writers, and performers is put under the umbrella of Big-C creativity. Small-scale creativity, which individuals express daily, for example when creating a small project during quarantine or solving a problem in a unique way, is referred to as Little-C creativity. **The focus of the dissertation is Little-C creativity, because I investigated creative solutions being applied in a small scale in a laboratory setting.**

1.3 Creativity as a complex construct

Creativity is a complex construct because creative solutions require complex thinking processes, such as DT (Gabora, 2019; Guilford, 1950; Mumford et al., 2003; Runco & Jaeger, 2012). Therefore, it is critical to investigate creativity as a complex trait across individuals. The Honing theory of Creativity (HT; Gabora, 2017) connects the concepts of complexity with creativity. The central idea of HT is that our minds evolve through self-organization by modifying their content to adapt to the new surroundings. The self-adaptive property of the mind is referred to as psychological entropy (Hirsh et al., 2012). Open and self-organizing systems such as living organisms continually interact with and adapt to their environments to minimize internal entropy. The open systems capture information from their external environment to maintain semi-

stable, equilibrium states, and displace entropy into the external environment to keep their own entropy at a manageable state. Psychological entropy has been redefined as arousal-provoking uncertainty which can be experienced negatively as anxiety or positively as creativity. The positive experience of arousal as creativity is consistent with findings that creative individuals exhibit greater openness to experience and higher tolerance of ambiguity (Feist, 1998) which could dispose them towards uncertainty states. Thus, higher variability in arousal reflects inclination towards situations which increases psychological entropy. Creative individuals experience such higher entropic states positively and try to resolve them (Hirsh et al., 2012). It has been proposed that creativity uses psychological entropy to drive emotions and intuitions which make greater contributions in tracking and monitoring creative progress. Thus, to summarize, HT holds that creativity originates from a higher entropic state experienced positively and hence, creative idea production can be seen as complex adaptation over time to uncertain environmental input. **Therefore, in the dissertation, creativity is conceived as a complex construct.**

1.4 The brain is a complex dynamical system

As described above, creativity can be conceived as a complex trait at the behavioral level. But can this complexity be measured at the neural level to establish brain-behavioral relationship of creativity as a complex trait? To investigate neural complexity, it is first important to understand the concept of complexity in the context of biological systems such as the human brain. Healthy biological systems are characterized as nonlinear dynamical systems. Dynamical systems theory of complexity (Stam, 2005) describes nonlinear dynamical systems as self-organized which refers to a set of processes in which order in a system emerges from constant interaction of its internal elements. Further, the systems are malleable, which means that they interact with the external environment to change, grow, learn, and evolve. The changes are integrated across multiple spatial and temporal scales. The self-adapting and self-organizing properties of dynamical systems make them complex over time. To get a sense of complexity in the real world, Tononi et al. (1998) provides an example: Gas at high temperatures is an example of randomness which demonstrates high complexity. Crystallized structures represent order or homogeneous behaviors which are repeated in space and hence, represent low complexity.

However, a critical point to note is that complex systems strive to be neither too complex nor too random, there is an optimal point between the two states. The human brain is an information processing system exhibiting the highest degree of complexity among human organs (Wang et al., 2018). The brain is a non-linear and complex dynamical system in which neurons fire together when they receive sufficient levels of inputs from other neurons. The neurons are interconnected to form specialized neuronal assemblies (functional segregation). Functional specialization as well as integration of groups of neuronal assemblies which take place at multiple spatial and temporal scales is a fundamental principle of brain organization. The functional segregation and their integration is a guide to adaptive behavior (Tononi et al., 1998). Further, local neuronal populations constitute intra-regional and inter-regional functional brain networks which non-linearly interact with each other to give rise to complex transient spatio-temporal fluctuations of electrical brain signals i.e., EEG signals. The nonlinear complexity of the EEG signals contains information about the architecture of the neural networks at multiple spatio-temporal scales. Therefore, EEG signals exhibit complex temporal fluctuations reflecting nonlinear dynamical processes. In neural network frameworks, such transient fluctuations tend to reflect transitions between network microstates that can be used as an estimate of brain signal variability and complexity.

The brain signal variability and complexity have been shown to be key components of healthy brain functioning (Garrett et al., 2011, 2013). Brain signal variability allows for the formation of functional networks and exploration of multiple stable functional states (Easson & McIntosh, 2019), whereas the brain signal complexity (BSC) reflects the brain's ability to adapt to unpredictable environments (Goldberger, 2006). Greater variability in the amplitude pattern of the signal over time indicates a more complex system (Deco et al., 2011; Heisz & McIntosh, 2013). Thus, the variability and the BSC derived from the EEG signals deliver important information about the underlying network dynamics.

Dynamical systems theory of complexity (Stam, 2005) divides interpretations of the complexity of the EEG signals into three types: 1) Resting state brain activity in healthy adults is characterized by high dimensional complexity but low synchronization of the neural networks; 2) Unhealthy or pathologic systems are characterized by hypersynchronous neural networks and thus, are highly

non-linear; 3) Degenerative systems are hyposynchronous with abnormally low synchronization. Therefore, healthy systems are characterized by intermediate levels or fluctuating levels of synchronization of the neuronal networks which leads to normal information processing. Neural signal variability and complexity have been suggested to be a proxy indicator and neural marker of the neural dynamic characteristics, cognitive performance, and even brain disorders (Garrett et al., 2011, 2013). In this framework, diseased and pathological systems are seen as the breakdown of nonlinear properties resulting in loss of variability and complexity(Gow et al., 2015; Lipsitz & Goldberger, 1992). Taken together, the brain is a large complex network of interconnected elements at multiple spatio-temporal scales which manifest complexity. The BSC can provide important information about network dynamics and mechanisms of the underlying brain signals (Courtiol et al., 2016; Heisz et al., 2012). **Building upon the theoretical views and empirical evidence reviewed above, I suggest that the BSC during creative task performance can be quantified in the EEG signals. Specifically, I sought to investigate the temporal BSC inherent in the EEG signals to capture essential features reflecting the internal functioning of the system focusing on creativity.**

1.5 Creativity arises from large-scale brain network activity

Individuals differ in their capacity to be creative. But what makes some individuals more creative than others? This intriguing question has been central to creativity research. The neural correlates of individual differences in creativity have been studied with several neuroscientific methods. The current state of knowledge on the neurophysiological basis of creativity divides into two explanations: A global or broad-network view and a local view (Abraham, 2018). The broad-network view of creativity has been put forward by the notion that creative idea generation involves simultaneous activations of widely distributed and time-variable neural networks. These neural networks involve the default mode network (DMN), supporting self-referential thought, introspection, and imagining the future; the executive control network(ECN) that modulates executive functions; and the salience network (SN) that monitors incoming information by prioritizing and distinguishing salient stimuli. These networks typically work in opposition to one another, and the degree to which their activation is synchronized within an individual

predicts the individual's creative thinking ability (Beaty et al., 2015, 2016, 2019). Hence, the global or broad-network view of creativity holds that creativity is a complex trait that emerges from large-scale neural assemblies working in synchrony during the time of heightened creativity. The local explanations of creativity are grounded on the involvement of localized regions of the pre-frontal cortex (PFC) which are dominantly involved during creative idea generation (Gonen-Yaacovi et al., 2013). The fact that there are multiple large-scale brain networks as well as small-scale localized brain regions associated with creativity is a confirmation that there are multiple processes belonging to creativity. Thus, due to the complexity of creativity and its neural underpinnings, a method is needed with which the dynamic interplay of local and global neural networks can be captured. BSC measures seem very suited to this purpose, as they allow to utilize information obtained from the spatial and temporal dynamics of the neural activation (McIntosh, 2019). BSC has previously been measured only in resting state as a predictor of creative performance (Ueno et al., 2015), however, it has not been measured during the performance of the creativity tasks. Therefore, **Study 2 investigates BSC during performance of a DT task. Overall, the dissertation combines the view of network neuroscience on creativity as a complex psychological construct requiring multiple brain networks and the HT which posits creativity at a macro level as a psychological entropic state. Therefore, in this dissertation creativity is conceived as a complex trait and investigated its neural correlates at micro level in the complexity in the EEG signals.**

1.6 The measurement of brain signal complexity (BSC) using Multi-Scale Entropy (MSE)

Complexity of a physiological system can be analyzed using entropy-based algorithms that quantify the regularity and predictability of time series (Costa et al., 2002). Entropy refers to the information content of a system in the context of information theory (Shannon, 1948). In this context, a physiological signal with higher entropy can be interpreted as having higher information processing capacity (Heisz & McIntosh, 2013). The conventional way of considering the link between entropy and complexity is to assume low entropy to characterize a highly predictable system which is less complex and high entropy to indicate more randomness and a

less predictable signal originating from the system. For example, traditional entropy measures in empirical data have assigned high entropy values to the pathological conditions like cardiac arrhythmia which are associated with high erratic fluctuations and low entropy values to health systems. Their output is related with high complexity due to adaptive capabilities in the changing environment (Costa et al., 2002, 2005). These results are theoretically challenging as literature hypothesizes that complexity of physiologic systems reflects its ability to adapt and function in an ever-changing environment (Friston, 2011). Physiological systems operate across multiple spatial and temporal scales which results in multi-scaled complexity (Sporns et al., 2000).

Multi-scale entropy (MSE) is an information-theoretic metric that provides an index of neural complexity across multiple spatiotemporal scales (Costa et al., 2002, 2005). The rationale underlying complexity measures is that healthy biological systems surpass functionally sub-optimal states showing higher diversity and complexity by embracing a broader range of dynamic variability, also facilitating the adaptability of a dynamical system (Costa et al., 2002). Therefore, better functioning systems should generate signals with higher complexity to enable a better response in a constantly changing environment. MSE is a popular neural marker of individual differences in brain signal variability and complexity. It is sensitive to aging, mental disorders and brain diseases (Garrett et al., 2013).

1.7 Calculation of Multi-Scale Entropy (MSE)

The MSE algorithm joins the calculation of Sample entropy (SampEn) with a coarse graining procedure which is similar to low-pass filtering. The SampEn, suggested by Richman and Moorman (2000) provides a quantitative index of a dynamical system's randomness or irregularity. It assigns large values to more complex signals and small values to random or highly deterministic signals (Costa et al., 2005). In general, signals such as neural oscillations and stationary signals that feature a repetitive structure are allocated lower entropy and hence, lower complexity. In contrast, highly irregular or non-repeating signals (less predictable) are assigned higher entropy, hence, higher complexity. However, random systems may display high complexity similarly to complex systems but this does not necessarily make them complex. MSE uses SampEn to define complexity as the unpredictability of the signal at a given time scale.

Therefore, an increase in SampEn will correspond to increased BSC. MSE algorithm consists of the following two steps:

1) Coarse-graining: The first step consists of down-sampling of the time-series similarly to low-pass filtering which produces multiple sub time-series of varying time scales (see Figure 1.1 for the illustration). Time-series at scale 1 is the original signal, then for each given time scale, non-overlapping sets of adjacent sample points are averaged together to form a new time series. This procedure is repeated up to the corresponding number of time scales of interest.
2) Calculating SampEn: In the second step, SampEn is calculated for each new coarse-grained time series produced in the first step. SampEn identifies repetitions of sequence patterns in the signal. There are two critical parameters in this step: m (pattern length) and r (threshold). Traditionally, the parameters are set to m = 2 and r = 15% of the SD of the original time series. The pattern length of m = 2 means that variability of the amplitude pattern of each coarse-grained time-series will be compared for two versus three consecutive data points. For example, in Figure 1.1, first the number of sequences with a data points satisfying the threshold (r) are counted and denoted as N(a) Then the number of sequences with a+1 length are counted and denoted as N(a+1). This counting is conducted up to N-m, where N is the length of the time series. This procedure is repeated for all the other matched sequences. For illustration, in Figure 1.1, Panel (b), in arbitrary unit numbers, with respect to the first two-point sequence (the green-orange dyad), there are three other two-point sequences that are identified as similar patterns based on r. With respect to the first three-point sequence (the green-orange-blue triad), there are two other three –point sequences that are identified as similar patterns based on r. Then, SampEn will be the natural logarithm of the ratio of two-component and three-component patterns i.e.,

$$SampEn(a) = -ln\frac{N(a+1)}{N(a)} \tag{1.1}$$

In the example, the SampEn will be a natural logarithm of the number of the dyad pairs (green-orange dyad) and triad (green-orange-blue) pairs.

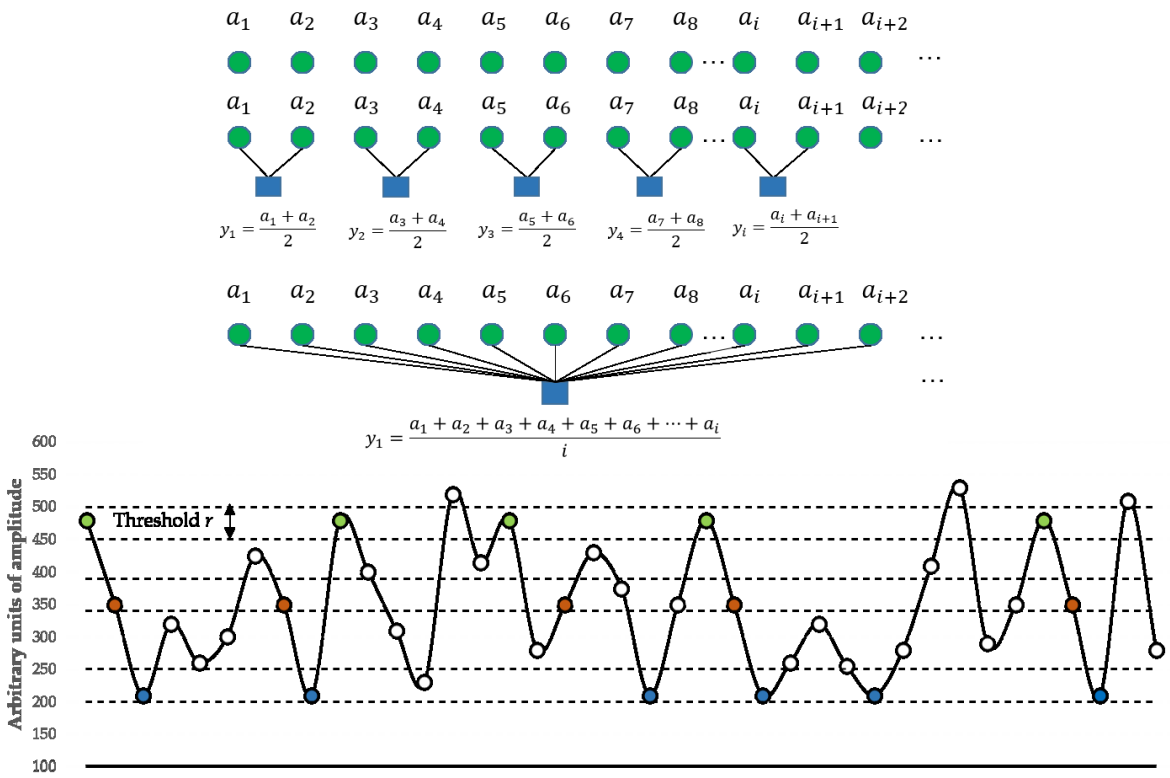

Figure 1.1. Illustration of Multi-Scale Entropy (MSE) algorithm. Panel (a) shows the first step of coarse-graining. Each box represents a data point. Panel (b) illustrates the second step in which the Sample Entropy (SampEn) of each coarse-grained time series is calculated ($m = 2$). This figure is an example with arbitrary data unit. In this example, with respect to the first 2-point sequence (the green-orange dyad), there are three other 2-point sequences that are identified as similar patterns based on the threshold r. With respect to the first 3-point sequence (the green-orange-blue triad), there are two other 3-point sequences that are identified as similar patterns based on r. Likewise, the algorithm will count the number of similar triad pairs (N3) and the number of similar dyad pairs (N2) from the entire sequence. SampEn is the natural logarithm of N2/N3.

Therefore, application of MSE on the EEG signals can capture the nonlinear dynamic activity patterns of the brain across multiple time scales. From a theoretical point of view, small time scales in MSE reflect local neural interactions, while large timescales reflect activity of widely distributed neural networks (Grundy et al., 2017 ; Vakorin et al., 2011). Linear stochastic effects are assumed to be related to observational noise at lower timescales. Coarse-graining applied during MSE analysis is essentially a down-sampling process, which alleviates linear effects in large timescales. Thereby, small timescale MSE extracts information from the whole frequency spectrum and also captures linear stochastic effects in the signal, while large timescale MSE relates to slow oscillations and reflects non-linear signal properties (Courtiol et al., 2016; Miskovic et al., 2019). **Therefore, by applying MSE to EEG signals recorded during creativity task, I aim to capture the stochastic properties of the EEG signals that are assumed to be associated with the joint**

neural activities of local (small scales) and widely distributed (large scales) brain networks. Thus, neural dynamics captured in MSE in creativity task at large timescales is interpreted as the activity of broadly distributed networks.

1.8 Relationship between creativity, intelligence, and cognitive control

"Learning more about a theoretical construct is a matter of elaborating the nomological network in which occurs" (Cronbach & Meehl, 1955, p. 187). Therefore, in order to understand creativity, it is crucial to examine and isolate its' closely related constructs. The dissertation specifically focuses on two closely related abilities: intelligence and cognitive control.

Recent psychological and neuroscientific investigations have provided evidence that intelligence and creativity are moderately and positively associated (Benedek et al., 2014; Silvia et al., 2015; Weiss et al., 2021). Often, intelligent solutions require creative ideas. Another potential discussion on this relationship is the shared but differential involvement of cognitive control (Benedek et al., 2014). Cognitive control is the process by which individuals can inhibit automatic responses and flexibly adapt to produce complex goal-directed behavior. Cognitive control encompasses inhibitory control or inhibition which refers to the process by which the cognitive system is guarded from salient but irrelevant stimuli (Jones et al., 2016). It has been suggested that inhibitory control is the common cognitive basis underlying the positive relationship between creativity and intelligence (Cassotti et al., 2016; Chrysikou, 2018). The increasing body of behavioral studies have converged on the notion that inhibition is required for creative idea generation as individuals need to inhibit typical or dominant responses in order to produce unique, creative ideas (Camarda et al., 2018; Zabelina & Ganis, 2018). Another line of theoretical argumentation proposes that the cognitive basis of creativity relies on the joint contributions of associative and executive abilities (Beaty et al., 2014). In this light, (Beaty, 2020) explains creative thinking as an interplay between memory and control systems of the brain. For example, in the Alternative Uses Task (AUT; Guilford, 1967), when individuals are asked to produce unusual usage of a common item, they usually first tend to produce typical uses which are retrieved from long-term memory. At this stage, memory plays a role because without knowledge, no ideas can emerge (Beaty, 2020). Then, in search of creative ones, the individual needs to overcome the salient

and known solutions to come to new ideas, requiring cognitive effort. Therefore, certain executive functions (inhibition and updating) are critical to generate creative thoughts (Diamond, 2013). To summarize, creativity and intelligence are moderately associated abilities that are required to solve problems logically and effectively. Cognitive control plays an explanatory role in this complex relationship. However, we still lack a detailed investigation of the association patterns between cognitive control and multiple facets of creativity measured by DT tasks (i.e., fluency and originality) and intelligence (i.e., gf and gc). **The dissertation additionally focuses on exploring the relationship between creativity, intelligence, and cognitive control extending to their facets at behavioral and neural levels focusing on BSC.**

1.9 Aims of the dissertation

Building upon the theoretical views of creativity and complexity, and empirical evidences suggesting that brain activation during creative activities involve intrinsic, widely distributed neural networks (Arden et al., 2010; Beaty et al., 2018; Jung & Haier, 2013), the current dissertation conceives of creativity as a complex construct and investigatesd creativity as a complex trait at the levels of brain and behavior. The dissertation aspires to answer the following research questions, motivated by the literature reviewed above:

1) Can MSE measures reliably and sensitively capture differences between specific states of the brain (i.e., EEG in resting state with open and closed eyes and during performance of task)?
2) Are scalp distributions of grand-mean MSE measures comparable between different recording conditions of EEG signals (in resting state with open and closed eyes, during performance of face and object recognition tasks, a verbal DT task, and during inhibition and non-inhibition conditions) and across different time scales?
3) Do individuals systematically differ or do they follow the same rank order in the MSE measures of resting state versus task processing states (in Study 1,2, and 3)?
4) Can BSC measured via MSE be considered as a neural marker of verbal creativity, inhibition, and intelligence?

These questions are addressed in thee empirical studies. First, **Study 1** investigates the reliability of MSE measures across different brain states (i.e., resting and task states in the EEG signals) and time scales of MSE. Specifically, the MSE was measured in resting state (closed and open eyes) and during performance of a face and object recognition task. **Study 2** combines dynamical systems theory of complexity and HT of creativity to parameterize complexity of the brain signals in creative brain states. Specifically, EEG was measured during performance of a verbal DT task in two conditions in which individuals were required to produce unusual, creative and usual, fluent verbal associations in response to presented nouns. BSC has previously been measured only in resting state as a predictor of creative performance (Ueno et al., 2015). Therefore, I expected the specificity of individual differences in MSE within different brain states to be predictors of creative potential as measured by verbal DT task. At last, **Study 3** examines the relationship between creativity, intelligence, and cognitive control. Specific executive functions such as inhibition and updating and cognitive control have been shown to explain the shared variance between creativity and intelligence at the behavioral level (Benedek et al., 2014). Further, cognitive control and creativity have been linked by a proposed mechanism that creativity is related to inhibitory control; Individuals need to inhibit irrelevant or common responses in order to create novel ideas. Therefore, the study first aimed to replicate the relationships between creativity, intelligence, and cognitive control extending it to their facets i.e., fluency, originality, gf, gc, and inhibition. Further, the study investigated the relationship between inhibition and creativity by examining their association at BSC level using MSE. However, prior to examining the relationship between creativity and inhibition at the BSC level, it had to be investigated whether MSE can be in general considered a neural marker of inhibition. Next, I investigated whether MSE in inhibitory brain states is a correlate of creativity. Finally, the study explores how MSE acquired in inhibitory and creative neural states are associated with individual differences in gf, gc, fluency, and originality measured with multiple independent behavioral tasks. Taken together, these studies provide methodological recommendations for future studies focusing on individual differences in terms of MSE-cognition and contribute to the knowledge on BSC perspective on creativity and its' relationship with creativity and intelligence.

2 The reliability and psychometric structure of Multi-Scale Entropy measured from EEG signals at rest and during face and object recognition tasks

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2.1 Abstract

Background: Multi-Scale Entropy (MSE) is a widely used marker of Brain Signal Complexity (BSC) at multiple temporal scales. Methodological improvement: There is no systematic research addressing the psychometric quality and reliability of MSE. It is unknown how recording conditions of EEG signals affect individual differences in MSE. These gaps can be addressed by means of Structural Equation Modeling (SEM).

Results: Based on a large sample of 210 young adults, we estimated measurement models for MSE derived from multiple epochs of EEG signal measured during resting state conditions with closed and open eyes, and during a visual task with multiple experimental manipulations. Factor reliability estimates, quantified by the McDonald's ω coefficient, are high at lower and acceptable at higher time scales. Above individual differences in signal entropy observed across all recording conditions, persons specifically differ with respect to their BSC in open eyes resting state condition as compared with closed eyes state, and in task processing state MSE as compared with resting state.

Comparison with existing methods: By means of SEM, we decomposed individual differences in BSC into different factors depending on the recording condition of EEG signals. This goes beyond existing methods that aim at estimating average MSE differences across recording conditions, but do not address whether individual differences are additionally affected by the type of EEG recording condition.

Conclusion: Eyes closed and open and task conditions strongly influence individual differences in MSE. We provide recommendations for future studies aiming to address BSC using MSE as a neural marker of cognitive abilities.

2.2 Introduction

Cortical areas in the human brain are interlinked by innumerable neuronal connections to form functionally specialized assemblies. These spatially and functionally interlinked assemblies operate at multiple spatio-temporal scales and give rise to complex spatio-temporal fluctuations of electrical brain signals due to nonlinear interactions among the excitatory and inhibitory neuronal activities (see Sporns et al., 2000 for a review). These spatio-temporal fluctuations reveal

important underlying dynamical information (McDonough & Nashiro, 2014; Ueno et al., 2015), because the intrinsic properties of a complex dynamical system ought to be manifested in the features of signals produced by it. Thus, understanding the spatio-temporal complexity of fluctuating neuronal signals can help to capture essential features reflecting the internal functioning of the system and to differentiate between optimal and sub-optimal states. Brain signals can be obtained non-invasively by the scalp Electroencephalography (EEG), which however, due to volume conduction has limited spatial resolution. In contrast, other measurement techniques of neural responses like functional Magnetic Resonance Imaging (fMRI) – which reflects brain activity via change in blood oxygenation – has superior spatial resolution but is limited in temporal resolution. Hence, indicators of spatio-temporal complexity of neural responses are usually derived as proxies using information from either the spatial or the temporal signal domain. Multi-Scale Entropy (MSE) is the state-of-the-art temporal Brain Signal Complexity (BSC) measure. It has been proposed by Costa et al. (2002) to quantify Sample Entropy (SampEn) of a system at multiple time scales (from fine to coarse time scales, also referred to as low to high time scales). The basic rationale of MSE is that a multi-scale analysis provides more detailed insight into the underlying biological processes as compared with single-scale methods. On the one hand, EEG signals at lower/fine time scales are thought to represent activities and fluctuations in local networks and coarser time scales represent activities across more widely distributed networks (Grundy et al., 2017; Vakorin et al., 2011). On the other hand, linear stochastic effects are assumed to be related to observational noise at lower time scales. Coarse-graining is thus essentially a down-sampling process which alleviates these effects in coarser time scales. Thereby, fine time scale MSE extracts information from whole frequency spectrum and also captures linear stochastic effects in the signal, while coarse time scale MSE relates to slow oscillations and reflects rather non-linear signal properties (Courtiol et al., 2016; Miskovic et al., 2019). In recent years, researchers became highly interested in establishing MSE as a biomarker of cognition, hoping that it can differentiate between healthy and disordered brain systems, and between different cognitive/conscious states (Dauwels et al., 2010; Garrett et al., 2013; Stam, 2005; Takahashi, 2013). A number of studies have applied MSE measurement and used temporal scale dependent complexity changes to differentiate EEG signals under normal and pathological conditions (for a review see Garrett et al., 2013), such as schizophrenia (Takahashi et al., 2010), depression (Okazaki

et al., 2013), autism (Bosl et al., 2011; Catarino et al., 2011; Ghanbari et al., 2015), Alzheimer's disease (Escudero et al., 2006; Mizuno et al., 2010; Yang et al., 2013) and its genetic risk (Yang et al., 2013). In addition, further studies reported that MSE can track the effect of maturation and aging (Lippe et al., 2009; McIntosh et al., 2008, McIntosh et al., 2014). In these series of studies, MSE at fine time scales showed an increase with early maturation, whereas at coarse time scales MSE decreased with maturation. Aging goes along with decreased MSE at fine and increased MSE at coarse time scales (McIntosh et al., 2014). Further MSE studies have been conducted to differentiate sleeping vs. wakefulness (Ma et al., 2018; Miskovic et al., 2018), open vs. closed eyes states (Hussain et al., 2017) and increased vs. decreased levels of learning during a face recognition task (Heisz et al., 2012). All these studies provided support for MSE as being a promising biomarker candidate of functional changes in brain signals.

2.3 Aims of the present study

Based on the findings such as those reviewed above, researchers tend to consider MSE as a promising biomarker candidate of specific cognitive activities (Garrett et al., 2013). Despite its utmost importance, there are, however, no comprehensive studies that evaluated the psychometric quality and the state dependency of individual differences in MSE – which are prerequisites for establishing biomarkers. Thus, it is yet to be explored 1) how reliably MSE can be measured across different data segments (multiple epochs of EEG signal) and 2) how overlapping individual differences in MSE are when the EEG signal is captured in different recording conditions (e.g., EEG signals being recorded at resting, or task processing state). This is to ask: Do people systematically differ or they follow the same rank order when computing MSE based on resting or task processing EEG signals? Hence, the present study aims to answer these questions and fill the gap of knowledge about MSE from an individual differences perspective – one of the preconditions for establishing MSE as a biomarker.

In the present methodological work we thus addressed the following research questions (2, 3, and 4 being basic psychometric questions) aiming to provide recommendations on the measurement of individual differences in MSE:

1) Are scalp distributions of grand-mean MSE measures comparable between different recording conditions of EEG signals and across different time scales?
2) Can MSE be reliably assessed within specific recording conditions of EEG signals at different time scales?
3) Are individual differences in MSE specific for different resting state recording conditions of EEG signals (closed vs. open eyes)?
4) Are individual differences in MSE within Task Conditions (TCs) specific, i.e., are they distinguishable between different TCs? Does potential task condition-related specificity depend on the scalp location and the time scales considered?
5) Can the Area Under the Curve (AUC) be established as an integrative MSE measure across time scales? This is relevant for hypothesis testing considering MSE as dependent variable, because a scale-wise parametrization is associated with challenges of dealing with multiple testing problems.
6) How strongly are MSE values as measured in resting vs. task processing recordings conditions related with each other?

2.4 Methods

We investigated EEG signals recorded during resting state conditions (with closed and open eyes), assuming that the brain is spontaneously active and displays spatio-temporally structured dynamics also in states implying no direct task processing (Sleimen-Malkoun et al., 2015). We additionally computed MSE based on EEG signals collected during visual task processing – thus, when the brain focused on a specific task. The task consisted of 16 TCs allowing a comprehensive comparison of MSE across different recording conditions (resting vs. task processing, along with their further specific sub-conditions). If the rank order of persons in MSE as measured in different recording conditions are completely overlapping, we would conclude that the same processes are being captured in terms of BSC, independently of the state in which the EEG has been assessed. Such a result would thus lead to the conclusion that it is irrelevant to distinguish between MSE measured in different recording conditions when the measure is targeted as a biomarker of individual differences in cognition. Please note that average MSE differences between recording conditions could indicate both:

1) that the same cognitive process, but to different magnitude, or
2) that a distinct process is captured by means of MSE across conditions. By adding the individual differences perspective, these two options of interpretation can be disentangled.

Therefore, to investigate the effect of different recording conditions on the variance across persons, we illustrate how Structural Equation Modeling (SEM; see further explanation below) can be effectively applied. This multivariate modeling approach can decompose the variance across individuals into components due to different measurement or experimental effects and can test relationships between those variance components. In this work, SEMs were applied for:

1) multiple time scales (see explanations below);
2) multiple scalp locations (40 electrodes distributed across the scalp); and
3) in multiple recording conditions of EEG signals.

We used unidimensional measurement models to unravel the psychometric quality of MSE within specific recording condition. More complex, so called nested factor models were used for variance decomposition across EEG recording conditions.

2.4.1 Experiment and data description

2.4.1.1 Face and object recognition EEG task

The experiment consisted of four memory tasks differing in memory load (low vs. high) and in whether they used faces versus houses as stimuli. All tasks were performed during EEG recordings. In the task with low memory load, 12 stimuli (faces or houses) had to be learned and to be recognized later amongst non-learned distractors. In the high memory load task, 36 faces or houses were learned and tested for recognition thereafter (See Figure 2.1). All participants completed each of the four tasks in separate blocks presented in a counterbalanced order.

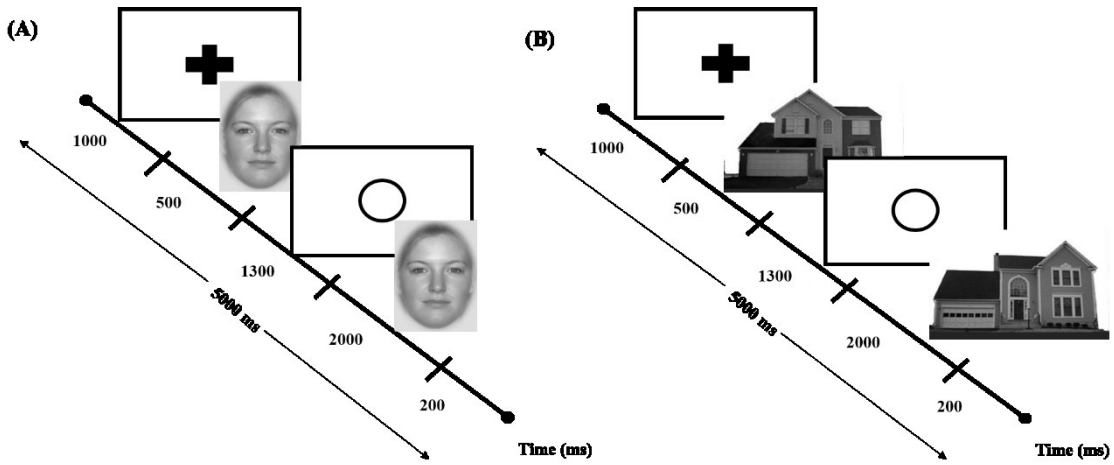

Figure 2.1. Illustration of trial sequence in the visual task. A) A trial with primed face. The beginning of a trial is indicated with a fixation cross shown for 1000 ms, followed by a primed face stimulus for 500 ms, which was replaced by a fixation circle for 1300 ms, followed by target face stimulus for 2000 ms. B) Shows the trial sequence with unprimed houses as stimuli.

Every block started with a learning phase for the memory set. During the learning phase, each stimulus was presented in a random order on the screen for five seconds and participants were instructed to actively memorize them by writing up some of their characteristics. During the test phase within the learning part of the task, designed to measure the achieved rate of learning, target stimuli were presented intermixed with distractor stimuli. Participants were asked to press the left or right button according to the position of the previously learned stimuli. The same test block was repeated with a different order of stimuli until participants achieved 80% or 100% accuracy in the high or the low memory load conditions, respectively.

After learning, a recognition phase followed which was designed as a priming paradigm. Stimuli (familiar or unfamiliar faces or houses) were preceded by a prime stimulus, which could be the same as the target stimulus (primed targets) where participant were instructed to press the right-hand button as fast as possible; or stimulus could be an unknown distractor (unprimed targets), where participants had to press the left-hand button. Familiar stimuli were those memorized in the previous learning phase, whereas the unfamiliar stimuli were new to the participants. In total, there were four conditions in each task, and along the memory load, there were 16 combinations of TCs. The abbreviations of these conditions are listed in Table 2.1 (column 4th & 5th) as they are used in the entire manuscript.

Table 2.1. Acronyms of the 16 Task Conditions (TC1 to TC16)

			Face (Fa)	House (Ho)
Easy (E)	Prime (P)	Familiar (F)	FaEPF	HoEPF
		Un-Familiar (uF)	FaEPuF	HoEPuF
	Un-Prime (uP)	Familiar (F)	FaEuPF	HoEuPF
		Un-Familiar (uF)	FaEuPuF	HoEuPuF
Difficult (H)	Prime	Familiar (F)	FaHPF	HoHPF
		Un-Familiar (uF)	FaHPuF	HoHPuF
	Un-Prime	Familiar (F)	FaHuPF	HoHuPF
		Un-Familiar (uF)	FaHuPuF	HoHuPuF

Note. The table aims to summarize the list of task condition (TC) acronyms as used throughout this manuscript

Each trial began with a black fixation cross presented for 1000 ms that was followed by a prime stimulus for 500 ms. Subsequently, the prime stimulus was replaced by a fixation circle presented for 1300 ms, followed by the target stimulus for 2000 ms. There were short breaks of 1 min. after blocks of trials in the recognition task part and a longer break of about 35 min in the middle of the experiment.

2.4.1.2 Sample

This is a reanalysis of the data collected by Nowparast Rostami et al. (2017) aiming to investigate individual differences in electrophysiological correlates of house and face cognition. When planning the study, a series of power analyses for Structural Equation Modeling (SEM; Muthén and Muthén, 2002) was conducted. Power simulation was carried out for models addressing brain-behavior relations including Event Related Potentials (ERPs) and a task battery of processing social and non-social stimuli. The models and effects (factor loadings on general and nested factors) postulated for those á priori power simulations are comparable in their size with those reported here. The power analyses suggested 200 to 250 participants to be required for acceptable power (> .80) to establish measurement models and brain-behavior relations. Therefore, EEG datasets were collected from N = 210 participants, most of them were of German ethnicity, including 50% females. Importantly, the power to identify nested factors with a loading above .45 (which is the main question for the present study) was above .95 even in case of 150

participants (power simulations can be provided to the reader on request). Some participants were excluded from the present analyses (see below), but the models were still adequately powered for the present research questions which so not include brain-behavior relationship analyses.

Participants' age ranged between 18–40 years (*M*age = 27.8; *SD*age = 5.4); educational background was heterogeneous (31% without high school degrees, 35% with high school degrees, 34% with academic degrees). Visual acuity was normal or corrected-to-normal with no history of psychiatric, neurological, genetic, or major systemic illnesses. 21 participants were left-handed and five were ambidextrous (Oldfield, 1971). Remuneration was 8 Euros per hour and in few cases consisted in course credits. Because the effect sizes (factor loadings) are similar in magnitude in case of ERPs (as measured by Nowparast Rostami et al., 2017) and MSE parameters, and because the present study is exploratory in nature, the size of the available sample can be considered as satisfactory for pursuing the present research aims.

2.4.1.3 EEG recordings

The EEG datasets were acquired using Ag/AgCl standard scalp electrodes with 40 electrodes mounted in an elastic cap (Easycap, Brain Products, Germany) in accordance with the 10 - 10 system (Pivik et al., 1993). The reference electrode (A1) was positioned on the left mastoid and electrode AFz was used as ground. Eye movements and blinks were monitored with electrodes positioned at the outer canthi of both eyes and below the right eye. Impedance was kept below 5 kΩ. The EEG was amplified using BrainAmp DC amplifiers (Brain Products, Germany) with a resolution of 0.1 μV at a sampling rate of 5 kHz and time constant of 10 s and 1000 Hz high cutoff. Then, the EEG datasets were down-sampled to 1 kHz and recorded in Brain Vision Recorder software (Brain Products, Germany). Resting state recordings were conducted before the cognitive tasks started. For a period of 90 s, every participant was instructed to keep the eyes open and do nothing. Subsequently, again for 90 s participants were asked to close their eyes and rest.

2.4.1.4 Data treatment

The preprocessing of the EEG datasets from resting and task processing recording conditions were performed with the Brain Vision Analyzer software and the EEGLAB toolbox (v13.5.4b; Delorme and Makeig, 2004) for MATLAB (2018, Math Works Inc., USA).

The preprocessing steps for resting state datasets were in line with the procedure used for the task state data. These were as follows: Down sampling from 1000 Hz to 250 Hz and filtered using a low-pass Hamming windowed sinc FIR filter with 40 Hz cutoff, and 12 dB/oct roll-offs (using EEGLAB function "eegfiltnew" by Widmann et al., 2015). We recalculated the data to average reference and removed linear trends. In the task data, we applied detrending from 2750 ms pretarget onset to 2150 ms post-target onset; in the resting state dataset, we performed detrending on every consecutive segment of 4900 ms. We removed trials from both (task and resting state) EEG segments with abrupt jumps between −200 ms to 2000 ms after stimulus onset, and rejected segments with data points departing from the segment mean with ± 80 μV and with a range exceeding 120 μV. The remaining, valid data resting state segments were concatenated. Next, in order to use long-enough data for MSE measurement models, participants with less than 10,000 concatenated resting state data points (40 s) were excluded, which resulted in the following sample sizes: 180 participants for resting state closed eyes, 197 for open eyes, and 206 for task data to be carried forward for MSE computation. For the resting state EEG data, the first four epochs of 10 s duration (2500 data points) were fed into MSE calculation, resulting in four independent MSE values to be used as indicators in SEMs (see further explanations of the SEM components in Section 2.6). The same treatment was conducted on the task data in which the preprocessed single trials were first concatenated. For the purpose of psychometric modeling, again the time series was segmented into four epochs of 10 s within each TCs. The resting and task EEG signal epochs used to calculate MSE, were of the same length including 2500 data points (10 s for each of the four epochs).

2.4.2 Multi-Scale Entropy (MSE) computation

MSE quantifies the temporal complexity of physiological signals at multiple time scales. The algorithm of MSE applied here strictly follows Costa et al. (2002). Concisely, the calculation at each time scale is implemented by the algorithm ("statistic") of SampEn suggested by Richman and Moorman (2000) and the calculation of the different time scales is implemented by coarse-graining. By using SampEn, MSE defines complexity as the unpredictability of the time series at a given time scale. More specifically, the algorithm of SampEn (see Figure 2.2 for illustration) identifies repetitions of sequence patterns in the time series and calculates the entropy in the following way: (1) count the number of sequences with m data points satisfying the similarity criterion (see the definition of similarity below) and denote it as N(m); (2) count the number of similar sequences in m+1 data points length, and denote it as N(m+1); (3) calculate the SampEn defined as the negative natural logarithm of the conditional probability that two similar sequences of m data points will be similar for the next 1 point :

$$SampEn(m) = -ln\frac{N(m+1)}{N(m)} \tag{2.1}$$

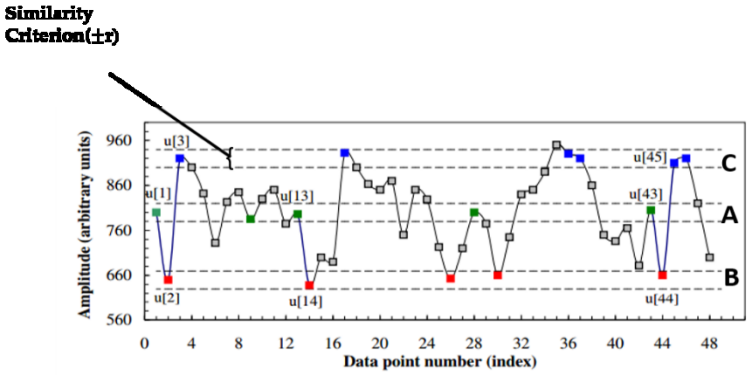

Figure 2.2. Illustration of Sample Entropy (SampEn) calculation (adopted from https://physionet.org/physiotools/mse/). The 3-points sequence u[1], u[2], u [3] is used as a template for pattern matching in this figure. The use of similarity criterion r is demonstrated as intervals A, B, and C between dash lines. The upcoming data points are matched within these intervals, and labelled with the same color (green, red, and blue). The 2-points sequences u[13], u[14] and u[43], u[44] are matched, and u[43], u[44], u[45] is a 3-points matched sequence. Thus, in this case the SampEn(m=2) = -ln (1/2). Conceptually, SampEn can reveal the predictability of a signal.

Regarding the similarity, two sequences (each with m data points) are similar if the differences between each of the paired data points of the two sequences (e.g., first point in the first sequence versus first point in the second sequence) are all less than r. Commonly, the parameters are set as

m = 2 and r = 15% of the standard deviation of the original signal (Costa et al., 2002), though the optimal parameter setting is still an open issue. The present work adopted this setting.

To capture the various features of nonlinear dynamical systems over a broad range of time scales and to differentiate from the unpredictable nature of white noise which, in principle is independent of time scales, MSE calculates the SampEn at multiple time scales. To this purpose, it is based on coarse-graining of the original signal while keeping the same similarity criterion r. Coarse-graining is implemented by replacing progressively increasing number of data points in non-overlapping windows by their average values (Costa et al., 2002) to form a new time series.

With different time scales there will be different number of data points which are used to estimate complexity, and thus, the reliability of MSE estimation (see Section 2.7.2 of Results) is expected to decrease across the time scales. For example, scale 1 (length 1) is identical to the original signal and scale 10 corresponds to averaging 10 consecutive data points of the time series. Thus, the total length will be reduced to 1/10 of the original signal. Since the temporal resolution of the original data is 4 ms (interval between successive points), scale 10 corresponds to a temporal resolution of 40 ms. We refer to the 10 scales as scale 1 to scale 10 throughout the article, where scales 1–5 are considered as fine/ lower and scales 6–10 as coarse/higher scales.

2.4.3 Analysis of individual differences in MSE by means of Structural Equation Modeling (SEM)

Statistical analyses were conducted with the R Software for Statistical Computing (R Core Team, 2017) using the package lavaan (latent variable analyses; Rosseel, 2012). For introductory text on SEM, we refer to Kline (2005). SEM is a generalized linear modeling framework combining factor analysis with path modeling. The key element in SEM is the latent factor, which in our case is the general MSE measured in different EEG recording conditions. One of our aims was to establish within condition measurement models of MSE that allow estimating factor reliability. Factors are estimated based on observed/measured proxies (Raykov and Marcoulides, 2012), called indicators. The SEM approach requires a minimum of four indicators for a latent variable to be identified on its own. We thus, parameterized four EEG signal epochs for each recording condition and measured MSE within each of those epochs. For example, in Figure 2.4A, the factor

called "MSE in a given brain state" is being estimated on the basis of four indicators (MSE parameterized in each EEG epoch as: MSE-segment1, MSE-segement2, MSE-segment3, MSE-segment4). SEM allows to quantify individual differences in specific clusters of multiple measures. It relies on the assumption that any measure we can think of can be decomposed into 1) true score (latent variable), 2) method or content specificity, and 3) measurement error. Given multivariate data (here MSE measured from EEG epochs from multiple recording conditions) captured at a given electrode, the intended variance decomposition can be carried out. 1) The true score is the estimated variance of the latent variable (here general BSC, independent of the recording condition); 2) Method or content specificity is reflected by the estimated variance of specific latent variables that capture shared variance across indicators of the same EEG recording condition (for example "Specific OE Resting State MSE" in Figure 2.4 B); 3) The estimated residual variance of the indicators reflect measurement error/ noise.

We explored the following SEM parameters in order to assess the psychometric quality of MSE in different recording conditions: (1) factor loadings and residual variances were used to compute reliability estimates of MSE measured in different EEG signal epochs (10 s) within the same recording condition; (2) specific factors, nested below general factors, and their variance across individuals are indicative for specificity of individual differences in MSE measured in different conditions; (3) factor correlations between latent variables representing resting vs. task processing conditions which inform about the specificity of individual differences in task processing vs. resting state MSE.

The evaluation of model fit was carried out through the following fit indices: $\chi 2$ –value, the Root Mean Square Error of Approximation (RMSEA < .08 for acceptable fit), the Comparative Fit Index (CFI > .95) and the Standardized Root Mean-square Square Residual (SRMR < .08).

The present research questions are all, except for the first one, related to individual differences in MSE. These questions will all be addressed by estimating a series of alternative SEMs. For research questions (2) to (4), we estimated three groups of measurement models are outlined below.

Figure 2.3A illustrates a one factorial measurement model intended to estimate the reliability of MSE, measured in different epochs of the EEG signal within a given recording condition addressing research question (2). We calculated reliability by means of McDonald's ω, which quantifies the amount of variance of all measured variables shared with the latent variable (a traditionally used definition of reliability, see e.g., Raykov and Marcoulides, 2012). The equation for the ω index is displayed in Figure 2.3A. To provide a comprehensive picture of reliability estimates, we calculated the ω values for MSE across the scalp (40 electrodes), for multiple time scales (scale 1–10), in different recording conditions. This resulted in two resting states + 16 task processing states = 18 estimates for each electrode and each time scale, thus, 40 (electrodes) * 10 (time scales) * 18 (recording conditions of EEG signals).

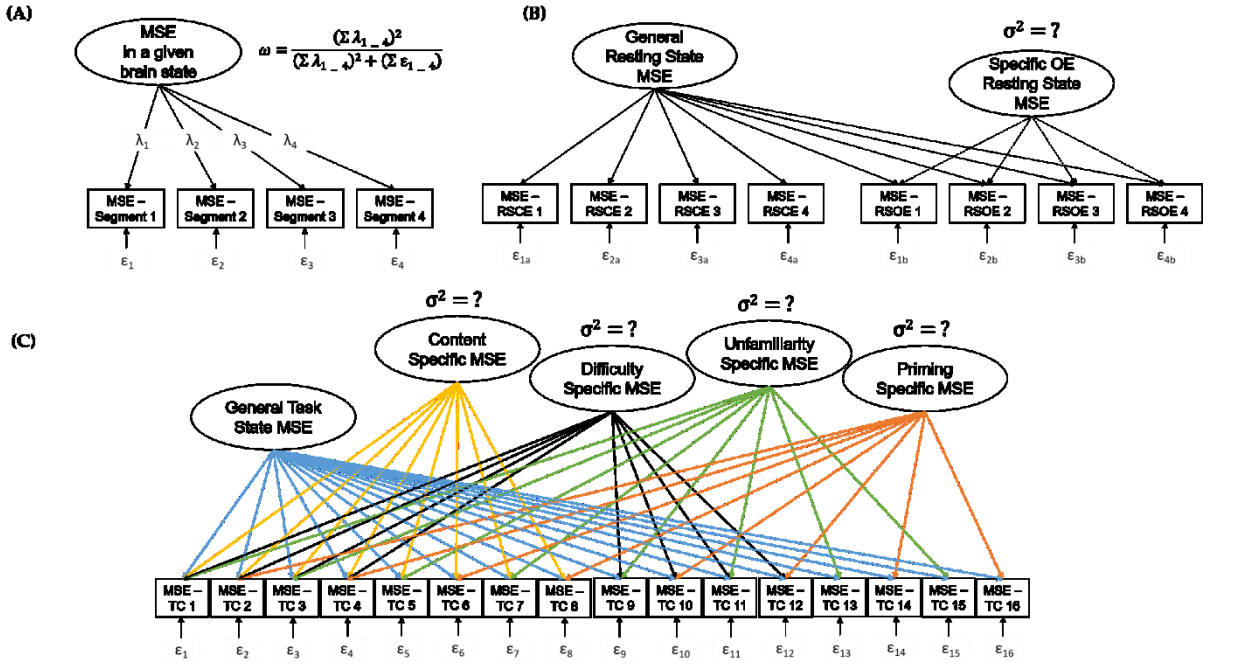

Figure 2.3. Schematic representation of the SEMs estimated for addressing research questions (2) to (4). Panel A – estimated model to address research question (2); Panel B – estimated model to address research question (3); Panel C – estimated model to address research question (4); MSE – Multi-Scale Entropy; MSE RSCE – MSE calculated in the Resting State Closed Eyes Condition; MSE RSOE – MSE calculated in the Resting State Open Eyes Condition; MSE TC – MSE calculated in the Task Condition (see Table 2.1. Acronyms of the 16 Task Conditions (TC1 to TC16), the numbers represent the 16 experimental conditions defined by the combinations of the four nested factors: Content [Face vs. House]; Difficulty [Difficult vs. Easy]; Unfamiliarity [Unfamiliar vs. Familiar]; Priming [Primed vs. Unprimed]); for example MSE – TC 1 represents the MSE calculated for an EEG signal epoch measured during face processing in the difficult task condition for familiar faces and in a primed condition (see the description of the experiment in the methods section); ω – Reliability estimate following the procedure by McDonald (1999); λ – factor loadings; ε – residual variance, indicating the amount of measurement error (unreliability) of a measured variable; σ2 – factor variance.

Figure 2.3B depicts the measurement model addressing research question (3). To this aim, we estimated two models that are inferentially comparable, based on the χ^2 -difference test ($\Delta\chi^2$). In the first model, only one factor – called General Resting State MSE – was estimated. This general factor captured MSE variance common for both resting state recording conditions of closed and open eyes. In the second step, we added an orthogonal second factor that indicated MSE in the open eyes recording condition only. If individual differences in MSE are partly specific in the open eyes recording condition as compared with the General Resting State MSE, this second factor will explain a substantial proportion of indicator variance and the two-factor model will better fit the data as compared with the more restrictive model including only one general factor. Thus, the $\Delta\chi^2$ will indicate statistical significance by the given difference in degrees of freedom between the two models (Δdf).

The SEM for addressing research question (4) is depicted in Figure 2.3C. This model follows the same logic of inferential model comparison like the one outlined in the case of the resting state data. However, in the task processing data we did not only have two, but 16 TCs. Consequently, four nested factors were added in a stepwise manner to the model. We added these specific factors (uncorrelated with the general factor and also orthogonal to each other) one by one without a specific order because the common systematic variance across all MSE indicators is already accounted for the general factor so that the order of including specific factors will not affect the results. These factors represent individual differences due to a given level of the recording condition as compared with the second level (e.g., processing facial stimuli as compared with house stimuli). With the content factor, we tested whether individual differences in MSE are specific for face as compared with house recognition. Likewise, with the difficulty, familiarity, and priming factors, we assessed specific variance due to these experimental manipulations.

To test whether individual differences in resting state, and TCs turn out to be specific at time scales 1–10, we estimated these two models for each of the time scale. By investigating specific electrodes, we assessed whether the model configuration differs in specific regions of the scalp.

For research question (5), we used AUC as an integrated measure of MSE across low and coarse time scales. For investigating the psychometric quality of AUC, we estimated the two factorial model for the task processing state MSE including a general factor and a nested factor accounting

for stimulus unfamiliarity (See Figure S2.1, online supplement A11; https://osf.io/b9h6g/), because this model turned out to best describe the task related MSE.

Finally, for addressing research question (6), the best fitting models for the resting state MSE at one side, and the task processing state MSE on the other side were related to each other in a comprehensive SEM (see Results section for details on the model configuration).

2.5 Results

Results are structured following the research questions. Representative parameter estimates are summarized in the Results section to serve for methodological recommendations. We additionally provide large sets of values and demonstrations with respect to psychometric analyses of MSE at single electrodes and multiple time scales in the Supplementary Materials. The present dataset of healthy young adults can serve as a baseline estimate of individual differences later across the lifespan. Thus, it can also be considered as baseline for future work aiming to target MSE as a marker of individual differences in elderly. For example, this study demonstrates the dimensionality of MSE to be considered in future investigations to target MSE as a biomarker for early detection of pathological aging due to Alzheimer's Disease.

2.5.1 Grand-mean scalp distributions of MSE across different recording conditions of EEG signals

To investigate whether grand-mean scalp distributions of MSE are comparable for the two resting (closed and open eyes) and task processing conditions, we calculated grand-mean MSE values for all participants for time scales 1–10 measured in the three recording conditions. Figure 2.4A displays the scalp topographies of the calculated grand-mean MSE values at time scales 2, 5, and 10. At scale 2, MSE is large in open eyes condition at temporal, and both, left and right frontal sites. MSE is lower at all sites in closed eyes condition and is the smallest in case of task processing condition. At scale 5, MSE is larger in open eyes, almost at all sites, and in closed eyes, it is larger in midline and frontal- central sites. In the task state, MSE is smaller as compared to both resting state conditions. At scale 10, MSE is larger in closed eyes, mainly concentrated at midline, frontal-central sites. Furthermore, it is larger in open eyes and is the lowest in task processing condition. Overall MSE values become larger after scale 5 in closed eyes than open eyes and are consistently

lower in task processing condition. Based on these topographies, we selected four representative electrodes Fz, T7, T8, and Pz which reveal four regional foci across the scalp. These foci are more clearly seen in low time scales. Figure 2.4B displays line plots together with error bars of grand-mean MSE for the two resting states and task processing conditions (averaged over all 16 TCs) across the 10 time scales for four representative electrodes. The error bars are calculated as the standard error of the grand-mean MSE values across participants. The line plots illustrate that MSE has consistently smaller values in task processing condition, regardless of electrodes and time scales. Closed eyes recording condition lead to larger MSE values for coarse scales as compared to open eyes and task processing condition, while open eye condition generated the largest MSE values for low scales < 5, especially at frontal and temporal, as compared with parietal sites. In summary, EEG signals in resting state conditions are less predictable and more complex than signals in task processing condition, where the EEG becomes more predictable and regular at most time scales > 2. Supplement A1 (https://osf.io/b9h6g/) provides topographies of grand-mean MSE for all other time scales and the three recording conditions of EEG signals which are not displayed here. Supplement A2 (https://osf.io/b9h6g/) provides the line plots with error bars for the rest of the electrodes. From the results above, we can conclude that scalp distributions of grand-mean MSE measures are comparable between different recording conditions of EEG signals (resting and task processing conditions), but the overall magnitude of MSE differs.

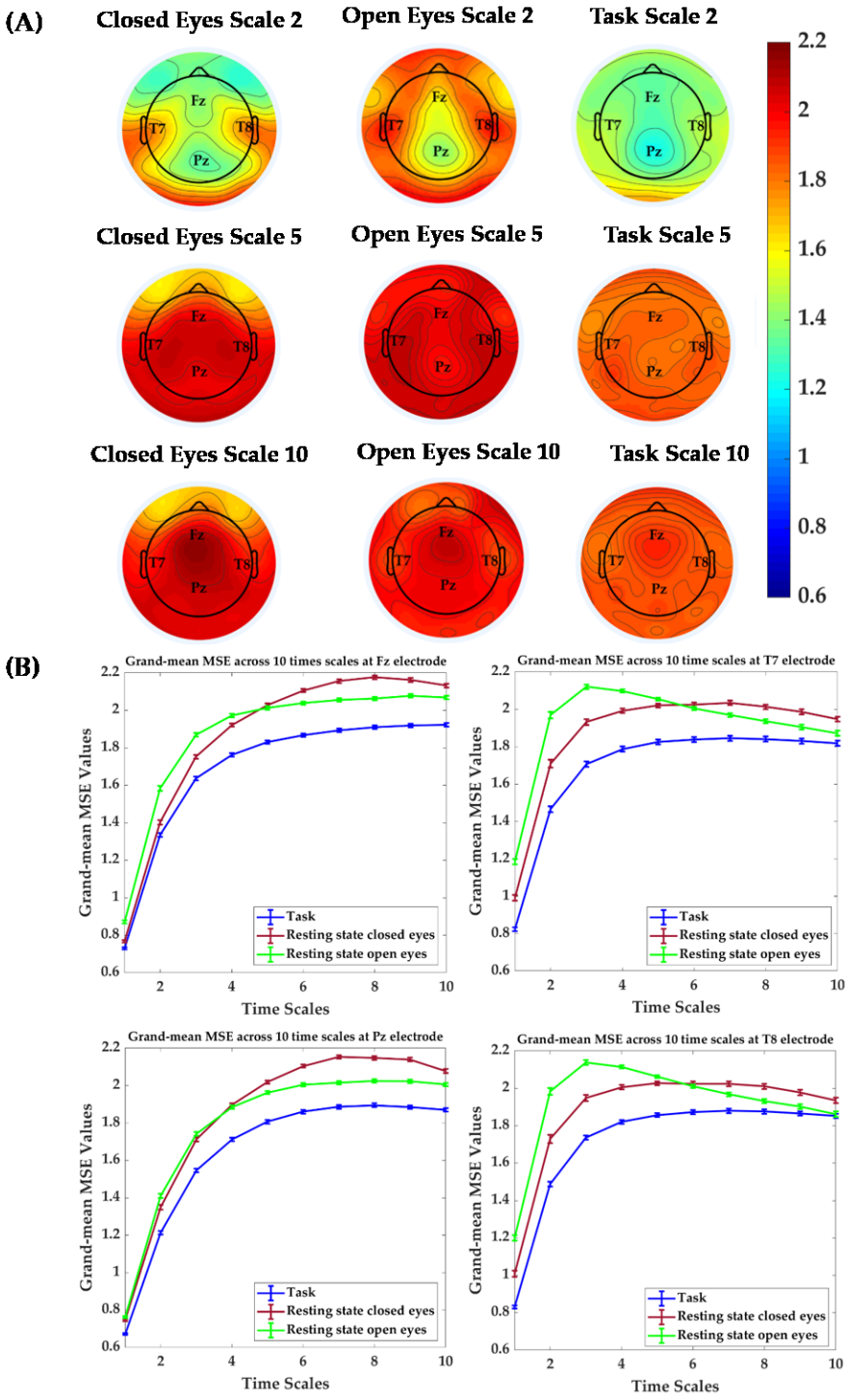

Figure 2.4. Spatial and temporal distributions of grand-mean MSE in different recording conditions of EEG signals. Panel A – Scalp topographies at scale 2 (first row), scale 5 (second row), and scale 10 (third row). The three columns represent closed eyes, open eyes resting state, and task processing condition (averaged over 16 TCs), respectively. Dark red color on the scalp topologies represent large MSE values and dark blue color shows small values. Panel B – Line plots of grand-mean MSE with error bars (standard error of the mean are calculated across participants and across 16 TCs) at 4 representative electrodes Fz, T7, T8, and Pz, and time scales 1–10, differentiated for three recording conditions in which EEG signals were recorded.

2.5.2 Within condition reliability of MSE

We next investigated how reliably MSE can be measured across different data segments (EEG signal epochs) captured in the same recording condition. We used McDonald's ω coefficient as reliability estimate. The coefficient ranges between 0 (entire non-reliability) and 1 (perfect reliability). The measurement model for reliability estimation was explained in the Methods section and is displayed in Figure 2.3A.

Figure 2.5 depicts the results on reliability in the same manner as the grand-mean MSE results have been displayed in Figure 2.4. Please note that the reliability estimates plotted in Figure 2.4 have been calculated based on factor loading estimates given by the measurement model depicted in Figure 2.3A. Figure 2.5A shows topographies of the MSE reliability estimates at low time scales to be high, evenly distributed across the scalp and to be comparable in magnitude across resting and task processing conditions. As time scale increases, reliability declines and starts to differentiate, both between scalp sites and recording conditions. Supplement A3 (https://osf.io/b9h6g/) provides reliability topographies for the rest of the time scales for three recording conditions of EEG signals which are not displayed here. Figure 2.5B displays the ω coefficients across time scales 1–10 at four representative electrodes. The line plots show the range (y axis) between 0.55 (threshold of acceptable reliability in terms of the ω coefficient) and 1 (perfect reliability). Supplement A4 (https://osf.io/b9h6g/) provides line plots of the ω coefficients for the rest of the electrodes. We provided reliability estimates for all time scales and electrodes in online supplement A5 for resting conditions and online supplement A6 for task processing condition.

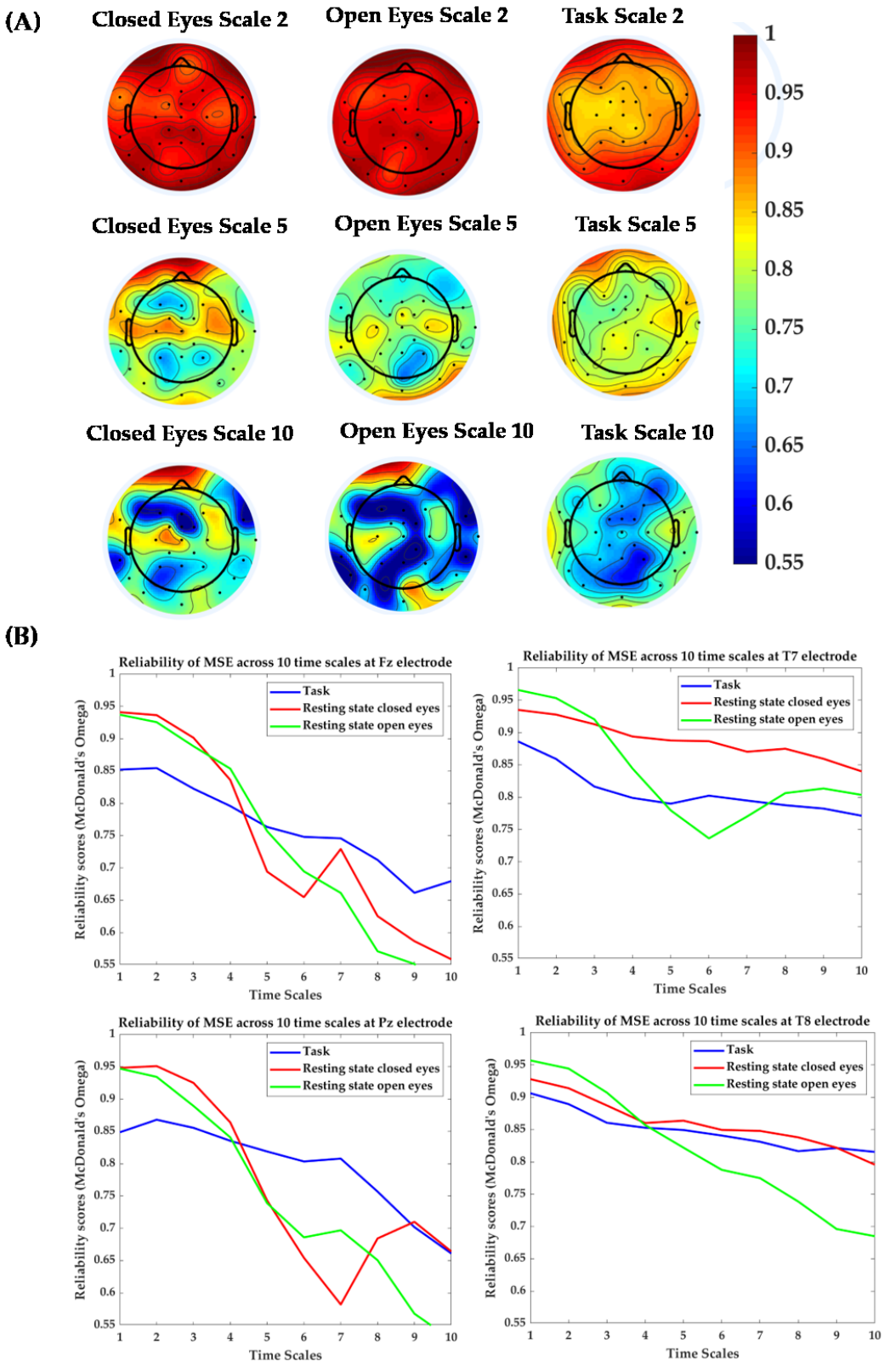
(A)
Closed Eyes Scale 2
Open Eyes Scale 2
Task Scale 2
Closed Eyes Scale 5
Open Eyes Scale 5
Task Scale 5
Closed Eyes Scale 10
Open Eyes Scale 10
Task Scale 10
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0.55
(B)
Reliability of MSE across 10 time scales at Fz electrode
Reliability of MSE across 10 time scales at T7 electrode
Reliability of MSE across 10 time scales at Pz electrode
Reliability of MSE across 10 time scales at T8 electrode
Task
Resting state closed eyes
Resting state open eyes
Reliability scores (McDonald's Omega)
Time Scales

Figure 2.5. Spatial and temporal distributions of MSE reliability estimates in different recording conditions of EEG signals. Panel A – Scalp topographies of reliability at time scale 2 (first row), scale 5 (second row), and scale 10 (third row). The 3 columns represent closed eyes, open eyes resting recording conditions of EEG signals, and task condition 1 FaHPF (face processing in the difficult task condition for familiar faces in a primed condition). Panel B – Line plots of MSE reliability at four representative electrodes Fz, T7, T8, and Pz, and time scales 1–10 differentiated for three recording conditions of EEG signals. MSE reliability is quantified by McDonald's Omega (ω) which is a point estimate based on individual differences in repeated MSE measures (four EEG epochs of each individual, thus no error bars can be computed).

2.5.3 Specificity of MSE recorded in resting state conditions

Next, we investigated the specificity of MSE measured in resting state recording conditions. Specificity would be reflected in potential non-overlapping variance between measures across individuals in open eyes as compared with closed eyes recording conditions. The model estimating the dependency of individual differences in resting state MSE (closed vs. open eyes) was explained in the Methods section and is displayed in Figure 2.3B.

To capture specificity, we estimated two models (one general factor called General Resting State MSE vs. an orthogonal factor above the general one capturing remained systematic individual differences after general MSE was accounted for – see Open Eyes Resting State MSE, in Figure 2.3B). Complete results including information about model convergence, factor loadings and the model fit are provided in supplement A7 (https://osf.io/b9h6g/).

The question was whether adding the specific factor to capture the difference between Open Eyes Resting State MSE as compared with General Resting State MSE in terms of individual differences would increase the model fit. Table S2.1 (online supplement A8; https://osf.io/b9h6g/) summarizes the results on model fit indices for representative electrodes Fz, T7, T8, and Pz and time scales 2, 5, and 10. According to the fit indices, the model quality was excellent for the two-factor model (all CFI > .96). The $\Delta\chi^2$, comparing the two models inferentially, was significant in all cases given a Δdf of four. This indicates that the two-factor model (Figure 2.3B) is a better description of individual differences in MSE as compared with the one-factor model (Figure 2.3A). More specifically, it indicates that the rank order of persons for MSE at rest with closed vs. open eyes is not completely overlapping because there is a qualitative difference between the two recording conditions.

Table S2.2 (supplement A8) provides standardized factor loadings onto the General Resting State MSE and the specific Open Eyes Resting State MSE for scales 5 and 10 at four representative electrodes. Loadings on the specific factor are considerable in magnitude and are significantly different from zero. Thus, the specific factor of open eyes MSE is identified. This observation holds across all time scales (See supplement A7, and – along with the model fit information provided above – it infers that in terms of individual differences, MSE measured during eyes open condition is not fully equivalent with MSE in closed eye recordings. Hence, future studies should consider specific effects of open eyes recording states when relating MSE with cognitive performance or other covariates of interest.

2.5.4 Specificity of MSE recorded in different task processing conditions

Next, we investigated the specificity of individual differences in MSE as measured in the task processing conditions. To this aim, we estimated a series of measurement models (illustrated in Figure 2.3C) based on the MSE values captured under different TCs (see Table 2.1). The model series was initiated with a general factor (General Task State MSE), and then further specific factors, orthogonal to the general one, were added incrementally one at a time. Thus, the model series comprised nested models that can be inferentially compared based on the $\Delta\chi^2$ -test. More specifically, the modeling included five steps. In step one, Model 1 estimated only a general factor; in step two, Model 2 included a general factor and an additional nested factor accounting for individual differences in face specific indicators (content specific MSE); in step three, Model 3 included both factors estimated in Model 2 and a further nested factor accounting for individual differences induced by increased task difficulty (difficulty specific MSE); in step four, Model 4 additionally assumed a factor accounting for stimulus unfamiliarity above all factors contained by Model 3 (unfamiliarity specific MSE); and finally, in step five, Model 5 included a general factor along with all nested factors estimated in Model 4 and one further nested factor accounting for individual differences due to the priming manipulation (priming specific MSE). Following previous ERP analysis by Nowparast Rostami et al. (2017) of this dataset, eight residual covariances were added to these models to achieve acceptable fit. They account for priming effects within experimental conditions. Thus, they indicate no global effect of priming, but a specific priming effect for otherwise the same factor levels (content, difficulty and familiarity; for example,

face – easy – familiar). Out of the five models, Model 1 does not fit the data well (but for Fz and Pz electrode). Model fit indices for four representative electrodes are displayed in Table 2.2.

Table 2.2. Model fit indices for Model 1 for time scale 5 at 4 representative electrodes

Electrode	$\chi 2$ [96]	CFI	RMSEA	SRMR
Fz	452.85	0.900	0.134	0.043
T7	758.87	0.833	0.183	0.067
T8	758.87	0.791	0.183	0.087
Pz	431.01	0.911	0.130	0.038

Note. $\chi 2$ – Chi-square/Ratio of $\chi 2$ to degrees of freedom (df); CFI – Comparative Fit Index; RMSEA – Root Mean Square Error of Approximation; SRMR – Standardized Root Mean-square Residual

Thus, we expected that additional factors accounting for experimental manipulations will improve the model fit. However, for electrode T8 and Pz, Model 2 and 3 did not converge at time scale 5 and, Model 3 and 4 did not converge at scale 10. The complete information on the results is provided in online supplement A9 (including all non-convergent models). Taken together, these results indicate that the addition of nested factors accounting for stimulus content, difficulty level and priming do not differentiate persons above the general individual differences in task processing MSE. Only the familiarity experimental manipulation systematically affects individual differences in MSE. The complete overview of parameter estimates are provided in Table S2.3 (online supplement A10) which shows that the model fit significantly increased by adding the unfamiliarity factor. Table S2.4 (online supplement A10) shows all factor loadings which are substantial in their magnitude. Fit indices revealed acceptable model quality (all CFIs > 0.90). The $\Delta\chi^2$, comparing the 2 models (1 and 3) inferentially, was significant in all cases (scale 5, 10 and for four representative electrodes) given the Δdf of 8. This indicates that the 2-factor model considering familiarity above a general factor is a better description of individual differences in task processing state MSE than the 1-factor model. More specifically, we can infer from the above results that the rank order of persons, when measuring MSE in trials with familiar vs. unfamiliar stimuli, does not completely overlap. However, no other TCs caused further specific individual differences after general differences in MSE and specific priming effects have been accounted for.

2.5.5 Area Under the Curve (AUC) as an integrative measure across multiple time scales of MSE

To avoid challenges due to multiple comparisons that occurs due to high dimensionality of the MSE measurement across scales, we used AUC to integrate across multiple time scales. The MSE algorithm provides multiple entropy values, one for each time scale. In this research, we estimated entropy at 10 time scales, resulting in 10 values for each individual within a given recording condition at a given electrode. It is, however, generally desirable to express entropy with a single value representing BSC. Hence, using AUC, one single value can be obtained which can then be used for statistical analyses, for example to investigate the psychometric structure of MSE and to relate MSE to behavioral variables.

The literature suggests to integrate MSE across time scales by measuring the slope of the entropy estimates across higher/coarse time scales (Takahashi et al., 2009). As displayed in Fig. 4B, MSE values are smaller for scale 1, and they increase steeply until scale 3 or scale 4, reaching an asymptote or at least levelling off at coarser scales (here, coarse scales being 5 to 10). For this reason of non-linear variation of entropy across time scales, we aimed to evaluate integrated scores across low and coarse scales separately. A simple measure to quantify such a functional shape is the AUC. The separate integration of entropy at low vs. coarse time scales is also motivated from a theoretical point of view. As suggested in the literature, low time scales reflect local neural interactions, while coarse time scales reflect activity of more widely distributed networks (Grundy et al., 2017; Vakorin et al., 2011), thus they have different interpretation. Therefore, we calculated two AUC values for every participant at the four representative electrodes considered in all previous models and within all recording conditions: 1) AUC as an integrated measure across low time scales 1 to 4, and 2) AUC as an integrated measure across coarse time scales 5 to 10. Next, we aimed to investigate whether AUC values are psychometrically sound measures of individual differences in MSE. For this we thus, estimated the 2-factor model (see Fig. S2.1, supplement A11) for the task processing state MSE including a general factor (GTask) and a nested factor accounting for stimulus unfamiliarity (Unfamiliarity specific MSE) for AUC of low and coarse time scales, separately. The model fit for low time scale AUC is displayed in Table S2.5 (supplement A11) and factor loadings are listed in Table S2.6 (supplement

A11). The model fit and factor loadings for coarse time scales are displayed in Tables S7 and S8, respectively. Results indicate that factor loadings for AUC measures are similar to those of single time scale MSE measures. However, in terms of model fit, the AUC based analyses revealed insufficient fit. Thus, we further examined modification indices to explore the residual covariance pattern that might have led to misfit. The modification indices suggested the following systematic pattern: Easy and difficult conditions of otherwise the same experimental levels of the factors content, familiarity and priming seemed to covary in their residuals (unique variance not accounted for by the general and unfamiliarity factor). Including these residual covariances hampered the model fit in both low and coarse time scales (See third row of Table S2.5 and S2.7 in supplement). Overall, the modeling of AUC values as integrated measures lead to the same conclusions on the psychometric structure of task processing MSE as derived from modeling individual differences at single time scales. However, modeling AUC values additionally showed that they result in psychometrically sound measures of individual differences.

2.5.6 The relationship between MSE measured in resting and task processing recording conditions for MSE of multiple time scales and AUC values

Finally, to investigate if it is necessary to consider task processing recording condition in MSE-cognition studies separately from resting state conditions, we assessed the relationships between the latent factors established in 2.5.3 and 2.5.4. To this aim we jointly estimated the two final measurement models describing the resting state MSE (general factor and a nested factor for MSE measured in open eyes condition) and the task processing state MSE (general factor and nested unfamiliarity factor). Parameters of interest were the correlations between the two general factors and the two specific factors. The model linking the two measurement models is depicted in Figure 2.6.

We provide correlation values in Table 2.3 for MSE values for multiple scales, and in Table 2.4 for AUC values for low and coarse scales, respectively. Table 2.3 illustrates that the general factors have strongest relationships but they share at most about 50% of their variance at the Fz electrode and time scale 5. Furthermore, Table 2.4 for single scale AUC indicators shows that only the general task and resting state factors are related (medium effect size, see first column of the table), whereas the two specific factors are not (second column). The shared variance between the general

factors however do not exceed 25%, indicating strong uniqueness of MSE measured during rest vs. task state.

Finally, in Table 2.5 we summarized fit estimates for the models as depicted in Figure 2.6 based on AUC indicators at low and coarse time scales and four representative electrodes. Fit estimates for single scales are comparable and are not provided for simplicity. Generally, the models fit best at frontal and parietal electrodes for high/coarse time scales AUC values (H.AUC)

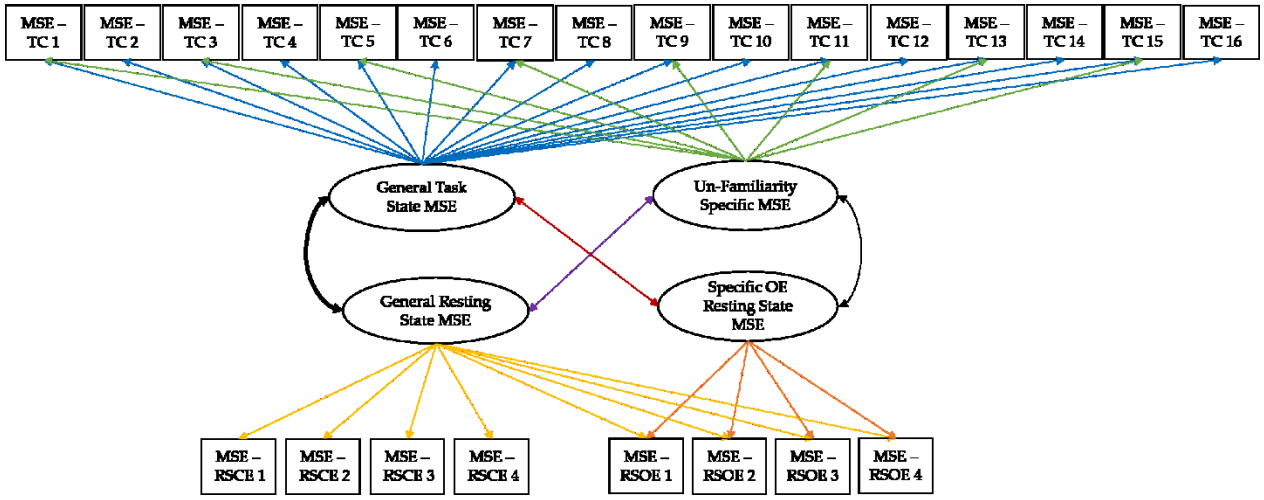

Figure 2.6. Schematic representation of structural model of relationship between resting and task processing conditions estimated for addressing research question (6). MSE RSCE – MSE calculated in the resting state Closed Eyes Condition; MSE RSOE – MSE calculated in the resting State Open Eyes Condition; MSE TC – MSE calculated in the Task Conditions (the numbers represent the 16 experimental conditions defined by the combinations of the four factors, TCs (see Table 1): Content [Face vs. House]; Difficulty [Difficult vs. Easy]; Unfamiliarity [Unfamiliar vs. Familiar]; Priming [Primed vs. Unprimed]); for example MSE – TC 1 represents the MSE calculated for an EEG signal epoch measured during face processing in the difficult task condition for familiar faces and in a primed condition (see the description of the experiment in the methods section). This model was applied to MSE values of multiple time scales and AUC values (integrated across multiple time scales).

Table 2.3. Correlations between latent factors estimated in the model depicted in Figure 2.6

Scale	Electrode	$r_{GTask\text{-}GRest}$	$r_{Unfam\text{-}OE}$	$r_{GRest\text{-}Ufam}$	$r_{GTask\text{-}OE}$
5	Fz	0.718	0.148	0.156	-0.013
	T7	0.246	0.142	0.041	0.335
	T8	0.435	0.174	0.148	0.074
	Pz	0.564	0.024	0.369	0.06

10	Fz	0.501	0.261	0.091	0.037
	T7	0.295	0.216	0.124	0.276
	T8	0.554	0.21	0.102	0.076
	Pz	0.525	0.045	0.372	0.02

Note. The table provides correlations between the latent variables estimated in the model depicted in Figure 2.6. $r_{GTask\text{-}GRest}$ – correlation between the General Resting State MSE factor and the General Task State MSE factor; $r_{Unfam\text{-}OE}$ – correlation between the Specific Open Eyes Resting State MSE factor and the Unfamiliarity Specific Task factor; $r_{GRest\text{-}Unfam}$ – correlation between the General Resting State MSE factor and the Unfamiliarity Specific Task factor; $r_{GTask\text{-}OE}$ – correlation between the General Task State MSE factor and the Specific Open Eyes Resting State MSE factor.

Table 2.4. Correlations between latent factors, estimated in the model depicted in Figure 2.6 based on AUC as an integrated measure across low (1-4) and high (5-10) time scales

Electrode	$r_{GTask\text{-}GRest}$ L.AUC/H.AUC	$r_{Unfam\text{-}OE}$ L.AUC/H.AUC	$r_{GRest\text{-}Ufam}$ L.AUC/H.AUC	$r_{GTask\text{-}OE}$ L.AUC/H.AUC
Fz	.503/.506	-15	.135/.313	.406/.485
T7	.483/.041	.182/.029	.145/.208	.250/.051
T8	.353/.257	.042/-.064	.152/.355	.103/.155
Pz	.444/.404	.220/.320	-0.62637363	.063/.591

Note. The table provides correlations between the latent variables estimated in the model depicted in Figure 2.6 when AUC scores for low and high scales are used as indicators. $r_{GTask\text{-}GRest}$ – correlation between the General Resting State MSE factor and the General Task State MSE factor; $r_{Unfam\text{-}OE}$ – correlation between the Specific OE Resting State MSE factor and the Unfamiliarity Specific Task factor; $r_{GRest\text{-}Unfam}$ – correlation between the General Resting State MSE factor and the Unfamiliarity Specific Task factor; $r_{GTask\text{-}OE}$ – correlation between the General Task State MSE factor and the Specific OE Resting State MSE factor; L.AUC as an integrated measure across lower time scales (1-4), H.AUC as an integrated measure across coarse time scales (5-10).

Table 2.5. Model fit indices for the measurement model of resting and task processing condition measurement model depicted in Figure 2.6 for AUC indictors (single scale AUC values) for low and high time scales

Electrode	$\chi 2[df=228]$ L.AUC/H.AUC	CFI L.AUC/H.AUC	RMSEA L.AUC/H.AUC	SRMR L.AUC/H.AUC
Fz	595 /384	.934/.962	.088/.058	.038/.050
T7	848/572	.900/.929	.115/.086	.049/.050
T8	871/562	.879/.920	.117/.084	.053/.044
Pz	524/460	.943/**.946**	.079/.070	.038/.049

Note. L.AUC: AUC measures across lower time scales (1-4), H.AUC: AUC measures across coarse time scales (5 to 10); CFI – Comparative Fit Index; RMSEA – Root Mean Square Error of Approximation; SRMR – Standardized Root Mean-square Residual.

2.6 Discussion

Because brain activity shows highly complex fluctuating patterns, suitable and reliable methods are needed for capturing these nonlinear dynamics. In the present study, the first of its

kind, we focused on the reliability and psychometric structure of a widely used algorithm quantifying biological signal temporal complexity – Multi-Scale Entropy (MSE). Our research revealed that the reliability of MSE measured from 10 seconds of EEG signal epochs is satisfactory across multiple time scales (1 to 10) and at all scalp locations, but it decreases across time scales. At low time scales, the reliability of MSE in task processing MSE is moderately low as compared with resting state. But at coarse time scales in resting state condition, MSE is more reliable at frontal, parietal, and right temporal scalp locations. By addressing six research questions and conducting comprehensive analyses of a large EEG dataset, we aimed to provide psychometric information about MSE. This knowledge is relevant to serve as methodological recommendations for future studies which aim to address BSC using MSE as a neural marker of cognitive abilities. In the following we will discuss our results with respect to the addressed research questions and derive methodological recommendations on their basis.

2.6.1 Grand-mean scalp distributions of MSE across different recording conditions of EEG signals

First, the scalp distributions consistently showed four main foci of signal complexity at anterior and posterior midline and bilateral temporal. These foci varied somewhat in their relative activities as a function of recording conditions and time scales, resulting in a shift in topography across MSE in different recording conditions. However, the differences between conditions are rather small in average across persons. By observing this systematic pattern of four foci, we conducted the psychometric analyses by selecting four representative electrodes belonging to each of these focal areas (Fz, T7, T8, and Pz). For comprehensiveness however, the supplements provide psychometric results for 1 to 10 scales and for 40 electrodes distributed across the scalp. Quite independent of time scales and scalp region, grand-mean MSE in both closed and open eyes resting states was somewhat larger than that during task processing condition. These findings are in line with the dynamical systems theory of BSC that assumes the state space of the signal to be most widely explored in the closed eyes condition; whereas in task processing condition, the interplay with visual input stimulus and related differentiation of neural networks during processing will limit the state space of the signal, generating patterns of lower BSC (see also Arsiwalla & Verschure, 2016). More concretely, because mental activity at rest is self-organized

by the underlying complex neural networks and is not strongly constrained by structured external stimulations, the brain's dynamical activity can freely explore a vast state space supported by the underlying network. Thus, the signal is diverse and highly complex (Allen et al., 2014) at rest. When a task is being processed, however, the brain's dynamic state space is constrained and limited by the stimuli that make the system to be more focused. Also, likely due to event-related components in the EEG signals resulting from task processing interaction of distributed brain networks, which are, somewhat, repeated in the experimental trials, BSC is reduced as compared with non-constrained (resting) recording conditions.

Following the same argument, resting condition with open eyes would also impose constraints on the recording conditions of EEG signals, thus, corresponds to lower MSE and BSC in a range of time scales, when compared with the closed eyes condition. However, the unstructured visual inputs at open eyes condition could induce additional fluctuations in the neural signals. In our data, the relative entropy difference measured during open and closed eyes conditions depends also on the scalp region. Especially at temporal sites and at low time scales, entropy is higher in eyes closed than eyes open condition. However, at certain scalp locations the difference is reversed at coarse time scales where, MSE becomes smaller for open eyes condition. This can happen if external unstructured visual signals induce fast neural activations (e.g., suppressing alpha waves and generating beta waves). This would contribute to larger entropy in low time scales, whereas more localized activations constrained by visual inputs would reduce entropy at coarse time scales compared with baseline wondering state across more distributed networks showing fluctuating activity in closed eye condition.

What are these findings suggesting for future studies? They indicate a slight quantitative difference between recording conditions of EEG signals used for MSE parametrization. This evidence is a first step for establishing qualitative differences between recording conditions based on MSE. A qualitative difference means that the measure (here MSE) does not only reflect more or less the same process, but potentially suggests that the experimental manipulation (e.g., rest or task) additionally activated an additional process that is qualitatively different as compared with the process induced by the baseline recording condition (see Oberauer, Wilhelm, & Schmiedek, 2005). However, based on mean differences we cannot separate quantitative from qualitative

differences between recording conditions. Thus, they cannot help us to unambiguously conclude whether MSE at rest reflects the same kind of network fluctuation as compared with MSE during task, or whether the captured complexity differences during task are due to qualitative differences between the brain networks involved in the given mental activity. However, additional investigation of individual differences as presented here allowed us to conclude which experimental manipulations/recording conditions lead to qualitative differences in MSE.

2.6.2 Within condition reliability of MSE

Second, in the present work we provided evidence on reliability of MSE when repeatedly parameterized on 10 time scales in relatively short time series of 10 s only (2500 data points; sampling rate of 250 Hz). If we use different, independent epochs of EEG signal**,** thus repeated measurements of MSE, the amount of true score variance is larger as compared with measurement error. Furthermore, we studied and provided comprehensive estimates of reliability depending on 1) the recording conditions, 2) scalp distribution and 3) time scales, showing that reliability is satisfactory in all conditions, but varies across scales and somewhat also across scalp locations at coarse scales. The spatial distribution of the reliability is not clearly structured.

For future individual differences research on MSE–cognition relationship, it is important to recognize that reliability decreases with increasing time scales or coarse-graining for both resting and task processing conditions. Because reliability places an upper limit on validity, it is relevant to have comprehensive reliability estimates before designing studies that relate MSE with cognitive performance. Our study showed that although the EEG segments are not very long, reliability turns out to be satisfactory. The reliability is expected to generally increase when considering longer EEG epochs for analysis, especially in coarse time scales. However, this option may not be valid in all conditions, since during long resting states the participants' brain could fall asleep (down state) temporally and locally (Vyazovskiy et al., 2011). Also, too long task performances could induce fatigue, which would lead to larger variability in the brain states across persons and reduce the reliability as defined for individual differences studies. Further systematic exploration of MSE reliability with respect to varied length of the time series, different recording conditions and sample sizes could be conducted in the future to provide additional

guidelines for designing individual differences studies on temporal entropy as a neural maker of cognition.

2.6.3 Specificity of MSE recorded in resting state conditions

Based on the grand-mean MSE, which is numerically largest in closed eyes resting condition (in coarse scales) and smallest during task processing condition (almost in all time scales), we can conclude that recording conditions of EEG have a quantitative impact on BSC. We interpreted the overall pattern of this quantitative impact in terms of dynamical systems theories, postulating that stimuli (structured or unstructured) focus the system's state and limit the diversity of the state space of the signal. This interpretation is obviously qualitative in nature. But grand-mean differences in MSE do not unambiguously let us conclude that a different state space is being activated at task as compared with resting state.

From an individual differences perspective, we further asked whether the recording conditions of MSE would also affect the rank order of persons. More specifically, the question is whether BSC will be differentially affected by recording conditions in case of different individuals. If so, we can conclude that recording conditions not only reflect quantitative differences in BSC, but also qualitative ones, because individuals would not rank differently on the two measures if only quantitative differences would be reflected in a measure as compared with the other measure (e.g., resting or task state MSE). In our analyses, the specific factor accounting for additional variance across persons in open eyes condition as compared with closed eyes explained a significant proportion of inter-individual variance over a general factor of resting state MSE. This additional factor may be explained for example, as reflecting individual differences, in the sensitivity to stimuli, attentional focus, or the interest taken in and knowledge about the environment (e.g., experimental cabin and paraphernalia). Thus, the quantified specificity of individual differences in MSE suggests that the two resting state recording conditions could serve as specific predictors for different aspects of cognitive abilities and related mental disorders.

There is an opinion in the literature suggesting the use of only one resting state condition in case of fMRI studies. The favored resting state recording condition is the open eyes condition, with or without visual fixation (Patriat et al., 2013). However, in light of the present findings, we learn that different resting state conditions have specific impact on individual differences and may turn

out in future studies to be specific predictors of cognitive abilities. Therefore, in seeking to establish relationships between resting state activity and psychological characteristics of individuals, using only one resting condition might be inadequate and limit the search space of potential MSE biomarkers.

2.6.4 Specificity of MSE recorded in different task processing conditions

The visual inspection of error bars of the line plots to compare different experimental task conditions (Figure 2.4B), showed that the grand-mean MSE does not differ across specific task conditions. However, there might still be systematic individual differences in MSE depending on experimental conditions if some individuals tend to have a positive and other a negative difference, leading to vanished mean difference in average but substantial variation across individuals. However, arguably such patterns are difficult to interpret. Whereas stimulus content, task difficulty (as manipulated by long-term memory load) and priming did not differentially impact MSE, individual differences were specifically affected by novel (unfamiliar) relative to familiar stimuli. Thus, the novelty of a stimulus differentially impacted the BSC across individuals. However, these individual differences are not reflecting variance around the same trend, for example, lower MSE for unfamiliar stimuli as compared with familiar ones across all individuals. The impact of stimulus novelty on individual differences in BSC is thus, only partly in line with our findings in open eyes resting state. When the brain is confronted with a novel stimulus, it will switch into a state, that is able to deal with such stimuli, limiting the state space of brain signal output, manifested by reduced MSE. However, this only happened in some individuals, whereas similar number of persons exhibited the opposite trend. This is arguably a finding that needs to be addressed systematically in future research.

In light of these findings we can derive further recommendations for designing studies on MSE. MSE specificity in terms of individual differences imply that the relationship with cognitive outcomes on the behavioral level may depend on the specific recording conditions of MSE within a given task. Consequently, studies on MSE and cognitive outcomes will need to systematically vary MSE recording conditions and obtain a comprehensive picture on how the MSE–cognition relationships depend on the task state in which BSC is measured.

2.6.5 Can an integrated MSE measure (AUC) be proposed across low and high time scales?

Additionally, to the above discussed study aims, for the first time in the literature on MSE, we proposed to use AUC as an integrated MSE measure across lower (scales 1to 4) and coarse (scales 5 to 10) time scales, to capture BSC related to more local circuit and more distributed network (Grundy, Anderson & Bialystok, 2017; Vakorin, Lippé, & McIntosh, 2011), respectively. The separation into two AUC measures, instead of one across all scales is also justified by the observation that there might be an interaction between time scale levels and recording condition of MSE (e.g., open eyes resting state MSE is larger in low scales, but smaller in coarse time scales, when compared with closed eye resting condition, with a cross-over around the scale 4 or 5, see Figure 4). Such an opposite pattern of MSE at lower and coarse time scales was previously found when comparing Alzheimer's patients with normal controls (Mizuno et al., 2010). Thus, a single AUC value across all scales would mask such interactions and would lead to wrong conclusions. Here, we found that both low and coarse time scale AUC are psychometrically sound measures of individual differences in BSC. Also, modeling individual differences in AUC leads to the same psychometric conclusions as the corresponding single time scale measures, but they do not have the disadvantage of multiple testing. Thus, if researchers are looking for integrated values to quantify and characterize individual differences in MSE aiming to avoid problems of multiple comparisons when many single scales are separately analyzed, the low scale and coarse time scale AUC values could be recommended to capture potential interactions between recording conditions and time scales.

However, note that other alternative integrative measures have also been proposed in the literature. When MSE was originally proposed (Costa et al., 2002, 2005), it was shown that for 1/f signals, MSE decays monotonically with time scales, thus it was proposed that the slope of decay of MSE curve at coarse scales can be considered as an integrative measure that captures the dependence between time scales (Takahashi et al., 2009). Our exploration using our data, however, showed that the estimation of slope using scale 5 to 10 or extending to coarse scales (e.g., up 20) is very unreliable in the 10 seconds EEG epochs (See Figure S2, Supplement E). A more

systematic evaluation of further integrative values of MSE measured in longer time series (longer EEG epochs) should be carried out in future research.

2.6.6 The relationship of MSE measured in resting and task processing recording conditions for MSE of multiple time scales or AUC values

We provided evidence for strong independence between resting state closed eyes and open eyes and task processing recording condition MSE in the perspective of individual differences. Again, this finding is invariant across time scales, but it seems that frontal electrodes capture a higher amount of overlapping variance between MSE at rest and MSE in task processing condition. The implications of these low correlations between resting and task processing condition MSE for the design and interpretation of future studies is obvious in the light of the above discussions. Existent and future studies providing evidence on the relationship between MSE–cognition may have very different meanings depending on whether MSE was measured at rest or during task processing condition.

However, a further implication of the present findings is also that task processing condition MSE is not entirely independent of resting state MSE, suggesting that persons with higher BSC at rest also tend to have more complex signals when working on a task. Thus, the BSC of task-free resting state could be used as a trait to partially predict task processing in individuals. Recent studies of fMRI data have confirmed this possibility using machine learning methods based on resting state functional connectivity (Tavor et al., 2016). How signal variability is related to functional connectivity is an interesting topic under investigations (McDonough & Nashiro, 2014; Wang et al., 2018).

2.7 Relationship of MSE to spatial properties

Brain activity is characterized by spatio-temporal complex patterns. It is a main goal in neuroscience to understand these complex dynamical networks which can reveal neural underpinnings of critical cognitive abilities, for example of creativity. However, current neuroimaging technologies are either limited in spatial resolution (e.g., EEG) or temporal resolution (e.g., fMRI). Thus, a direct assessment of spatio-temporal complexity of the brain signals is typically infeasible. A recent study using high spatial and temporal resolution voltage

imaging data in mouse brain showed that both, the temporal complexity measured by MSE and spatial synchrony measured by functional connectivity can reflect the underlying spatio-temporal variability (Liu et al., 2019). The high temporal resolution of EEG allows to study complexity in temporal domains, and the signals at different scales thus may reflect neural interactions across different spatial scales. Our study reveals that MSE and its reliability are spatially distributed and specifically modified by the tasks conditions, which suggest that different recording conditions of EEG signals may have different spatio-temporal complexity.

How spatio-temporal dynamical complexity of the brain would differ in individuals in different recording conditions across different spatio-temporal scales, remains an open question. Dynamical and critical system theory may provide a principle understanding but, an empirical study with high spatio-temporal precision technique, for example, fMRI-EEG co-registration could provide comprehensive characterization of this spatio-temporal dynamical complexity. Future studies thus, may investigate the relationship between the temporal signal complexity measured using MSE from EEG signals and the spatial interaction measured by functional connectivity in the perspective of individual differences.

2.8 Conclusions

This exploratory research on the psychometric quality of MSE was conducted to derive methodological recommendations for future studies and to better understand few existing studies on MSE–cognition in the framework of individual differences. We offer an interpretation on why resting state MSE and task processing MSE differs on the level of the grand-mean and the inter-individual variance. The complex spatio-temporal patterns in the brain will represent high dimensional state space. However, MSE measured using scalp EEG, is a smeared representation of the signal complexity due to its limited spatial resolution. This indicates that persons with similar MSE measure could still have different states in the high dimensional space. The individual differences analyses revealed that MSE can be established as a trait measure of individuals. Additionally, the interaction with visual input (open eyes resting state) or the task stimuli could also be different in their novelty, which can lead to differences in MSE measures in task induced states and to differentially impact on the MSE–cognition relationship.

2.9 Author notes

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3 What does temporal brain signal complexity reveal about verbal creativity?

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3.1 Abstract

Recent empirical evidence reveals that creative idea generation builds upon an interplay of multiple neural networks. Measures of temporal complexity yield important information about the underlying mechanisms of these co-activated neural networks. A few neurophysiological studies investigated brain signal complexity during the production of creative verbal associations and resting states, aiming to relate it with creative task performance. However, it is unknown whether the complexity of brain signals can distinguish between productions of typical versus original verbal associations. In the present study, we investigated verbal creativity with Multi-Scale Entropy (MSE) of EEG signals, which quantifies complexity over multiple time scales, capturing unique dynamic features of neural networks. MSE was measured in verbal Divergent Thinking (DT) states while emphasizing on producing either typical verbal associations or original verbal associations. We hypothesized that MSE differentiates between brain states characterizing the production of typical versus original associations and is a sensitive neural marker of individual differences in producing original associations. Results from a sample of N = 92 young adults revealed slightly higher average MSE for original as compared with typical association production in small and medium time scales at frontal electrodes and slightly higher average MSE for typical association production in higher time scales at parietal electrodes. However, measurement models failed to uncover specificity of individual differences as MSE in typical versus original associations was perfectly correlated. Hence, individuals with higher MSE in original associations condition also exhibit higher MSE during the production of typical associations. The difference between typical and original associations MSE was not significantly associated with human-rated originality of the verbal associations. In sum, we conclude that MSE is a potential marker of creative verbal association states, but replications and extensions are needed, especially with respect to the brain-behavior relationships.

3.2 Introduction

3.2.1 Creativity as a complex trait

Creativity is a complex construct, defined as the process of producing an original and appropriate outcome (Mumford et al., 2003; Runco and Jaeger, 2012; Gabora, 2019). Creative solutions require complex thinking processes, such as divergent thinking (DT; Guilford, 1950). The creative process includes various aspects, such as fluent idea production, flexibility of thought, degree of elaboration, and originality of ideas (Guilford, 1956; Guilford and Merrifield, 1960). Previous research often focused on the study of fluency, that is, the ability to produce many ideas in a short amount of time, and originality, characterizing the quality of an idea. The answers given in DT tasks are mainly evaluated by humans (Silvia et al., 2008), especially when it comes to judging the product of a creative thought process in terms of its originality. Thus, human ratings of task outcomes are also customary in neuroscience (see Fink and Neubauer, 2008).

In general, healthy and functional biological systems are highly complex resulting from the long process of evolution and self-organization (Lewis, 2000, 2005). Advancement of functions or emergence of new functions is, thus, associated with increased system complexity during the evolution process. It has been proposed that the human brain is an adaptive system where highly complex neural networks may produce similarly complex psychological states and activities, such as consciousness and creative thought (Laycraft, 2009). In a similar vein, the Honing theory (HT) of creativity proposed by Gabora (2017) links complexity-related concepts with creativity, suggesting that human minds are self-organizing, self-maintaining, and self-producing complex systems that subserve creativity. More concretely, the central idea of HT is that our minds evolve through an adaptive self-organization process in response to unpredicted (novel) environmental inputs, leading to a state of psychological entropy (Hirsh et al., 2012). This entropic state fosters creativity and aims to return to an equilibrium for further adapting to the environment. Hirsh et al. (2012) described psychological entropy as anxiety-provoking uncertainty, whereas Gabora (2017) redefined this assumption by replacing anxiety with arousal, conceptualizing creativity as a process of managing the state of psychological entropy in a positive sense. Empirically, this idea is supported, for example, by the fact that creative individuals exhibit greater openness to experience and higher tolerance to ambiguity (Feist, 1998). Honing theory seeks to explain how

ideas evolve over time considering the brain as a self-organizing complex system, which continuously interacts with and adapts to the environment to minimize psychological entropy. The theory aims to illustrate that psychological entropy is a driver of creativity impelled by emotions and intuitions (e.g., Cropley, 2006; Gabora, 2017) that plays a key role in monitoring and tracking creative progress. Following a similar line of theorizing, in the present research, we propose that the concepts of HT can be applied to understand the temporal complexity of EEG signals during creative verbal associations. More concretely, we assume that the challenge of solving a DT task applied in a laboratory setup will increase psychological entropy, which will be reflected in the brain signal during the time of dealing with this challenge. Thus, in analogy to the HT aiming at explaining the creative process on a larger timescale across human evolution, in the present research, we focused on production of creative verbal associations at shorter timescales, defined as the time of generating a specific idea in response to a laboratory EEG task. To this aim, we adapted a well-established verb generation task (from Prabhakaran et al., 2014), requiring to produce a verb that is semantically related to a presented noun. This task is easy to administer despite the constraints of neural data acquisition. It was originally designed to evoke brain activity associated with semantic processing (Petersen et al., 1989) but was modified to assess creative verbal association production. In general, creative verbal production is a well-investigated instance of creativity. Therefore, we manipulated psychological entropic states by asking individuals to produce answers in two conditions: either original (by making original verbal associations) or typical associations (by recalling the first verbal association that comes into mind). EEG has been widely and fruitfully applied in various creativity studies to capture the complex and transitory brain activity during creative idea generation. Stevens and Zabelina (2019) reviewed creativity studies that used EEG and summarized its advantages to assess fast-moving and complex brain activity during the creative process. In the here applied task paradigm, we expected to differentiate the two creative task conditions at the neural level in terms of temporal complexity of the EEG signal. We further postulate that the EEG-captured brain signal, recorded while an individual generates original associations, will differ from the signal during states of generating merely typical associations. Therefore, EEG complexity should be higher during original verbal association states.

3.2.2 Verbal creativity and brain signal entropy

In human brain cortical areas are interconnected by numerous neuronal connections which form specialized neuronal networks. These networks are characterized by complex non-linear dynamic patterns. The interaction between various excitatory and inhibitory reentrant loops in these networks cause transient fluctuations in the brain signals over time, such as synchronous oscillatory activity (Friston and Price, 2001). Such transients are believed to reflect transitions between network microstates that can be used as an estimate of complexity underlying the network. Hence, greater variability in the amplitude pattern of the signal over time indicates a more complex system (Deco et al., 2011; Heisz et al., 2012). Healthy brain functioning has been characterized by two key components, variability and complexity of neural signals. The variance in neuroimaging time series data or neural signal variability has been suggested to be a proxy indicator of the neural dynamic characteristics, cognitive performance, and even brain disorders (Garrett et al., 2011; Garrett et al., 2013). In a similar vein, BSC has been explored as a possible neural correlate of cognitive performance. Entropy based methods have been also used to examine brain signal variability and complexity, aiming to establish relationships with creativity. For example, Shi et al. (2019) used entropy measures of fMRI data to characterize the resting-state temporal dynamics and found a small-to-moderate positive association with verbal creativity. Sun et al. (2019) reported a correlation between verbal creativity and the temporal variability of functional connectivity patterns in the control network. In a similar line of research, a BSC measure known as MSE has been considered a potential EEG correlate of creativity. MSE is an information theoretic metric that provides an index of network complexity across multiple spatiotemporal scales (Costa et al., 2002, 2005). It uses sample entropy (SampEn) to quantify the irregularity of a time series at each of several scales achieved by coarse graining the original signal. A study by Ueno et al. (2015) showed higher MSE in resting-state EEG across large temporal scales in more creative as compared with less creative elderly individuals. Given the limited number of studies showing an association between verbal creativity and brain signal variability/complexity, we intended to further investigate this intriguing association by assuming that MSE can serve as a neural marker of verbal creative performance assessed with a DT task in younger individuals.

3.2.3 Global and local neurophysiological explanations of creativity

Recent neuroimaging studies have allowed a better understanding of network dynamics and brain regions involved in creative ideation. Abraham (2018) summarized and divided the current state of knowledge on the neurophysiological basis of creativity into global- and local-based explanations. Global explanations view creativity as being grounded on large and widespread systems in the brain. According to these explanations, creativity is not composed of one but a series of multiple, simultaneously operating processes. Thus, the complex trait of creativity emerges from large-scale neural assemblies working in synchrony during the time of heightened creativity. In this line, a review by Beaty et al. (2019) elaborated on the creative network dynamics and demonstrated that the executive and default mode networks can reliably predict creative thinking ability of individuals. They argued that creativity is a result of the interaction between associative and executive processes. A functional connectivity study by Beaty et al. (2018) revealed that creative ability was associated with activity in interacting brain regions including the default mode, central executive, and salience networks, supporting the broad network view of creativity. A meta-analysis of functional imaging findings on creativity by Gonen-Yaacovi et al. (2013) identified a set of frontal and parieto-temporal regions activated during tasks that engage creative thinking. Local explanations of creativity focus on elucidating the specific brain regions involved in creative cognition, which have shown distinct contributions of the prefrontal cortex (PFC; for a review see Dietrich and Kanso, 2010). Frontal areas such as the Brodmann area 10 (BA 10) is regarded as an integrator of the output of many cognitive operations (Ramnani and Owen, 2004; Abraham, 2018). The BA 10 has been shown to be active during creativity tasks that require the integration of weakly related concepts during creative idea generation, conceptual expansion, musical improvisation, and analogical reasoning (Abraham et al., 2012b; Beaty, 2015; Abraham, 2018). Furthermore, lesions in the PFC have been associated with low performance in many creative cognition tasks, such as fluency and originality (see Abraham et al., 2012a). Additionally, ventrolateral and dorsolateral PFC areas located posterior to the frontal pole were shown to be involved in creative story writing and conceptual expansion, as well as in processing metaphors (Abraham et al., 2012b; Kröger et al., 2012; Gold et al., 2012). Thus, our hypotheses in the present study are built upon a global view on creativity, which we approach by using multiple timescales

explicitly indicating spatial interactions in neural systems and not only temporal ones (Liu et al., 2019). Local explanations of creativity are reflected in our approach by as we specifically focus on prefrontal brain activity.

3.2.4 Aims of the present research

Building upon the theoretical views and empirical evidences reviewed above, in the current study, we explored verbal creative word generation as an integrated activity of widely distributed but predominantly prefrontal neural networks. To this aim, we applied MSE analysis that has been proposed to quantify temporal complexity in EEG signals. MSE parameterizes the complexity of temporal patterns underlying any kind of time series. When applied to brain signals, MSE provides information reflecting the communication of different neural generators in functional brain networks across multiple timescales (Heisz and McIntosh, 2013). From a theoretical point of view, small timescales in MSE reflect local neural interactions, while large timescales reflect activity of widely distributed neural networks (Grundy et al., 2017; Vakorin et al., 2017). Linear stochastic effects are assumed to be related to observational noise at lower timescales. Coarse-graining applied during MSE analysis (see "Materials and Methods" section for details) is essentially a down-sampling process, which alleviates linear effects in large timescales. Thereby, small timescale MSE extracts information from the whole frequency spectrum and also captures linear stochastic effects in the signal, while large timescale MSE relates to slow oscillations and reflects non-linear signal properties (Courtiol et al., 2016; Miskovic et al., 2019). Therefore, by applying MSE to EEG signals recorded during typical vs. original associations, we aimed to capture the stochastic properties of the EEG signals that are assumed to be associated with the joint neural activities of local (small scales) and widely distributed (large scales) brain networks. We thus interpret activity of broadly distributed networks on the basis of MSE at large timescales. Assuming MSE to be a neural marker of creative cognition, we hypothesized:

1) A quantitative MSE difference, in the sense that efforts to produce original verbal associations will lead to higher average MSE as compared with typical verbal associations.

2) We expected brain states during the production of original associations to qualitatively differ from brain states during typical association production, which might be reflected in specific rank orders of individuals with respect to their MSE in these two states.
3) We further expected the stronger MSE difference between typical and original associations to especially occur at frontal areas.
4) We aimed to explore whether the MSE difference between typical and original association states is associated with performance in terms of originality ratings of the produced associations.

3.3 Materials and methods

3.3.1 Participants

The sample of the present study consisted of $N = 101$ participants (51 females). In the following steps, we merged the behavioral data (human-rated originality scores of verbs) with the EEG acquired during verb associations. We excluded eight participants with less than 10 years of German language speaking experience and one case of invalid EEG event markers. Thus, the final sample included $N = 92$ participants (43 females, *Mage* = 23.88, range = 18–32 years); 89 individuals were native German speakers; 8 had not obtained high school degrees, 67 had high school or equivalent degrees, and 17 had academic degrees (e.g., bachelors, masters, or diploma).

3.3.2 Neurophysiological recordings

Electroencephalography datasets were recorded in a closed, quiet, and well-illuminated room using the Brain Vision Recorder software (Brain Products, Germany). The EEG signals were amplified using BrainAmp DC amplifiers (Brain Products, Germany) with an amplitude resolution of 0.1 mV. We used 0.16 and 1,000 Hz as low and high cutoff filters, respectively, and a sampling rate of 250 Hz. An EEG cap (Easycap, Brain Products, Germany) was mounted with 30 Ag/AgCl electrodes, placed according to the 10–20 system. Eye movements and blinks were monitored with electrodes positioned at the outer canthi of both eyes and below the right eye. The A1 electrode (left mastoid) was used as online reference, and AFz served as ground. Impedances were kept below 5 kΩ.

3.3.3 Preprocessing of electroencephalography data

Offline, the EEG signals were filtered using IIR (zero phase shift) and Butterworth filters between 0.1 and 50 Hz (order = 2; time constant = 1.59 s) and recalculated to average reference using Brain Vision Analyzer (Brain Products, Germany). Further preprocessing steps were executed in EEGLAB (Delorme and Makeig, 2004); SASICA (EEGLAB plugin; Chaumon et al., 2015) was used to remove eye blinks, movement, and electro-cardiac artifacts. We applied SASICA on the basis of autocorrelation measures and focal topography. Noisy components like muscle movements tend to show low autocorrelation. Therefore, muscle artifacts were detected by measuring the time-point by time-point variability, which was captured by low autocorrelation measures. Tonic muscle artifacts were detected based on their noise patterns and focused topography on electrodes around the edge of the EEG cap. Since the time window for the MSE analyses was defined from the onset of the stimulus until the onset of the participant's typing response (see Supplementary Figure S1), the probability of muscle movement artifacts during this interval was very low.

3.3.4 Tasks and procedure

In the verb generation task, there were two types of color-cued nouns presented: purple and green. To purple-cued nouns, participants were expected to produce typical associations—we thus instructed them to type in the verb that first came to their mind when being presented with the noun. To green cued nouns, participants should produce original, unique verb associations in response to the noun (see Figure 3.1). We modified the original task by translating the stimulus material (adapted from Prabhakaran et al., 2014) into German and dropping some nouns that were not proper in the German language (Supplementary Material S1 https://www.frontiersin.org/articles/10.3389/fnbeh.2020.00146/full#supplementary-material) for the list of original English nouns and their German translations with additional explanations for dropped trials). This resulted in 35 purple- and 32 green-cued nouns, signaling the production of typical and original associations, respectively. The task started with verbal instructions followed by an example trial and five practice trials. Participants were instructed to type in only one associated verb for each presented noun. The onset of the stimulus and the onset of participant's

typing response were time-marked, to be taken as signals of interest for MSE analysis. There were no time limits during the experimental trials in order to capture the brain activity during the complete creative verbal association production. PsychoPy (Peirce and MacAskill, 2018) was used to present the stimuli and record the behavioral data. EEG was recorded during the entire task, which lasted for ~20 min, depending to some extent on the participant.

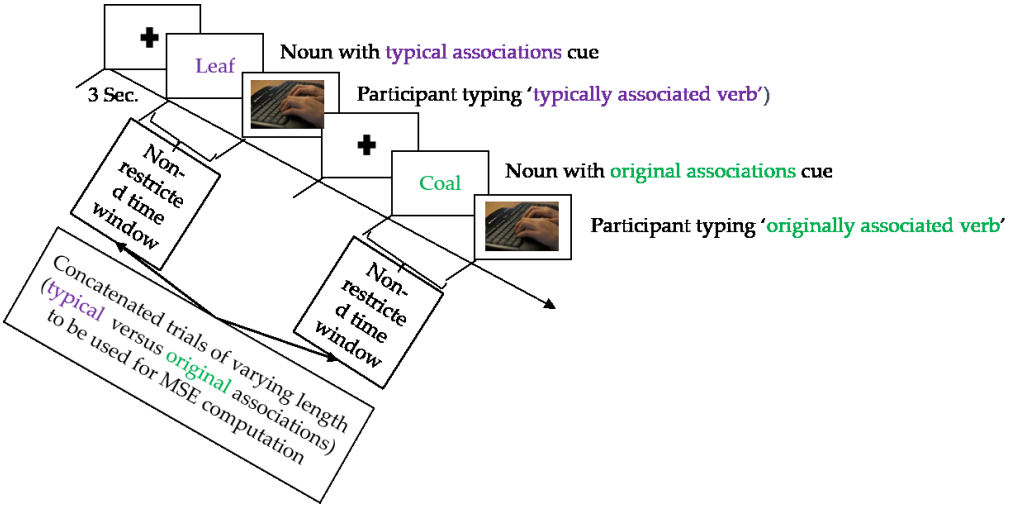

Figure 3.1. Illustration of the trial sequence in the verb generation task employed during the electroencephalography (EEG) recording session. The task began with a fixation cross presented for 3 s, followed either by a purple colored noun, called 'typical associations cue,' to which participants should produce a commonly known association, or by a green colored noun called 'original associations cue,' to which participants were expected to produce an original association. There were no time limits for the responses.

3.3.5 Human ratings of the verb production task outcomes

Three trained native German speakers rated all verbs produced during the task for originality. The raters were aware of the condition of origin of each verb but were instructed to rate the originality of the provided answer without taking the condition into account. The originality was assessed on a scale from 1 (not at all original) to 5 (unique and original), according to subjective scoring guidelines usually deployed in DT tasks (Amabile, 1982; Silvia et al., 2008). Such scoring guidelines usually explain that a highly original answer is an answer that is rare in the sample, remote from the presented noun and somehow unexpected for the rater (Silvia et al., 2008). Raters were instructed to use the total range of the scale if possible and to rate the generated verbs in relation to the answers provided by other participants. The intraclass correlations (ICCs; Shrout and Fleiss, 1979) across a fixed set of raters for all items ranged from 0.81 to 0.97. Due to this

sufficient/good agreement between the three raters, we used an average score across all three raters per item for statistical analyses (see Figure 3.2). We label human ratings of the verb production task outcomes in the entire manuscript as "human rated originality scores in typical associations and original association's condition."

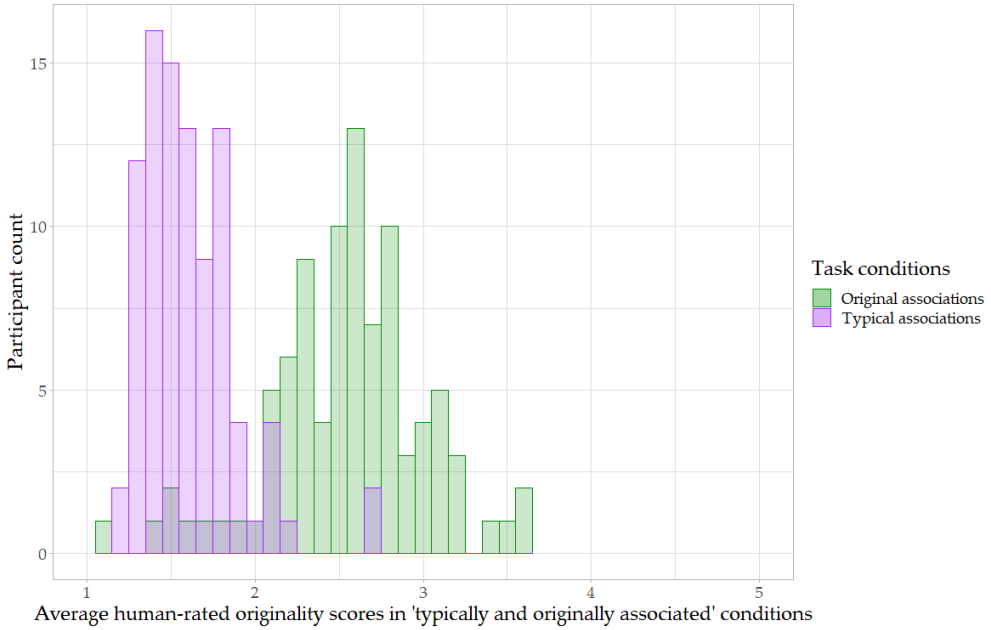

Figure 3.2. Distribution of average rated originality obtained across the condition-specific items of the verb generation task, across participants. Taken together, the histograms illustrate the participants more often produced original associations in the condition in which original associations were expected.

3.3.6 Multiscale Entropy algorithm

We calculated MSE, following Costa et al. (2002, 2005), in two steps.

1) We first coarse-grained the original signal at different timescales—a procedure similar to low-pass filtering. The coarse grained time series at timescale 1 is identical to the original signal; for obtaining scale n, the time series was divided into non overlapping concatenating windows, each of which contains n points where n is the corresponding scale. Within each window, all data points were averaged, forming a new coarse-grained time series at that scale (for illustration, see Figure 3.3A).
2) SampEn was then calculated for each of these coarse-grained time series (Figure 3.3 B). SampEn characterizes the entropy of a time series by calculating the recurrence probability

of a specific dynamic pattern. Specifically, SampEn identifies repetition of sequence pattern in the time series and calculates entropy in three steps, as follows:

(i) first, the number of sequences with m data points satisfying the similarity criterion are counted and denoted as N(m);

(ii) the number of similar sequences with m+1 data points length are counted and labeled as N(m+1); and

(iii) in the last step, SampEn is calculated as the negative natural logarithm of the conditional probability that two similar sequences of m data points will be similar for the next m+1 points.

$$\text{SampEn}(m) = -\ln\frac{N(m+1)}{N(m)} \quad 3.1$$

The two sequences are similar, if the difference between every point in the first sequence [N(m)] vs. the corresponding point in the second sequence [N(m+1)] are less than r (see Figure 3.39). There are two critical parameters in SampEn calculation: m (pattern length) and r (similarity criterion). We adapted the conventionally used parameter settings, m = 2 and r = 15% of the *SD* of the original time series.

3.3.7 Mapping the Multiscale Entropy timescales to real time

Multiscale entropy timescales (ranging from 1 to 20 in our study) can be mapped to real time. For example, according to the sampling rate (250 Hz) used in the present research, the real time sampling interval at scale 1 is 4 ms. Therefore, MSE at scale 1 reflects dynamical activities of the neural system at a resolution of 4 ms, which is fast dynamics. In a similar vein, scale 5 reflects dynamical activities of the brain at a resolution of 20 ms, and scale 10 indicates activity at 40-ms resolution. At the highest scale 20, the activity is at 80-ms resolution, which reflects slow brain dynamics. Thus, at smaller timescales, MSE reflects fast and, hence, local neural activities, whereas at larger scales, MSE captures slow dynamics across broader spatial domains.

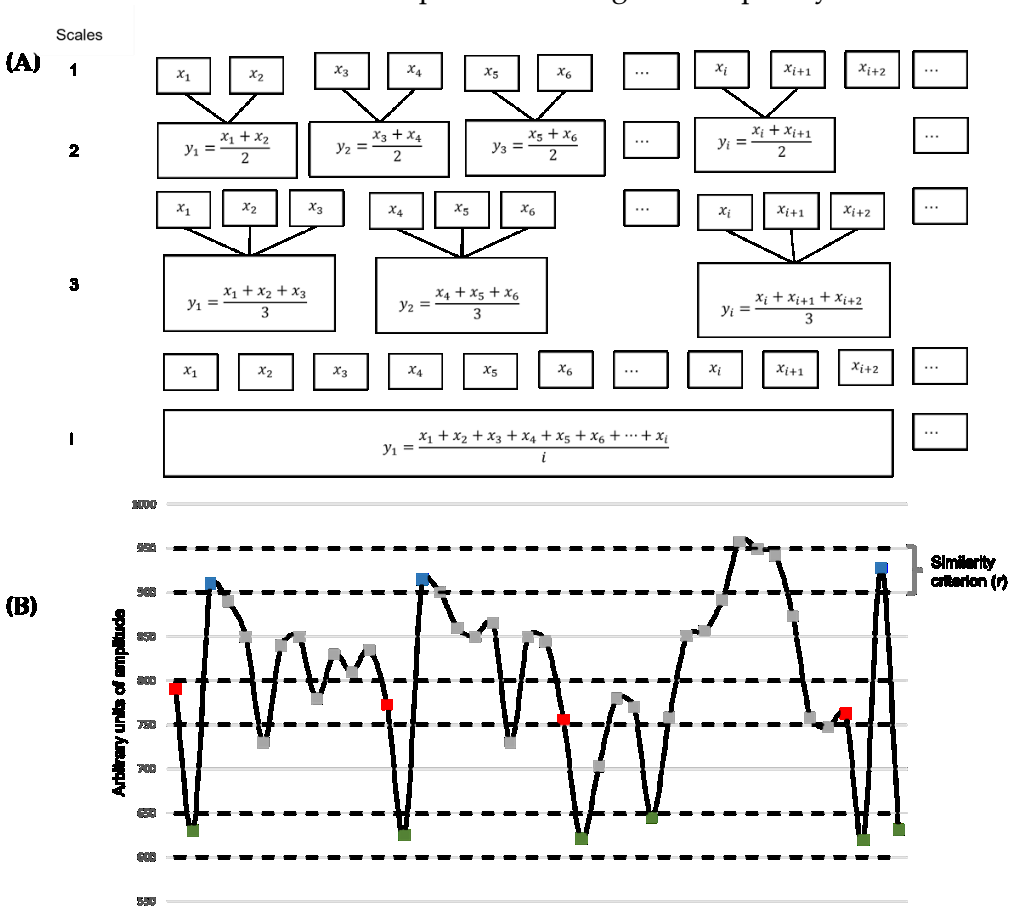

Figure 3.3. Illustration of multiscale entropy (MSE) algorithm. (A) Shows the first step of coarse-graining. Each box represents a data point. (B) Illustrates the second step in which the Sample Entropy (SampEn) of each coarse-grained time series is calculated (m = 2). This figure is an example with arbitrary data unit. In this example, with respect to the first two-point sequence (the red–green dyad), there are three other two-point sequences that are identified as similar patterns based on the threshold r. With respect to the first three-point sequence (the red–green–blue triad), there are two other three-point sequences that are identified as similar patterns based on r. Likewise, the algorithm will count the number of similar triad pairs (N3) and the number of similar dyad pairs (N2) from the entire sequence. SampEn is the natural logarithm of N2/N3.

3.3.8 Multiscale Entropy during production of typical and original associations

The trial length of the EEG recorded during the production of typical and original associations varied from trial to trial and person to person. The variation was inherent to the non-restricted response time (see Supplementary Figure S1, visualizing the average reaction times across all trials of "typical" and "original" association conditions across all participants; the figure shows that participants took a variable amount of time to provide their answers). For this reason, a decision had to be made whether to consider trial-to-trial and person-to-person variable trial lengths for MSE analysis or to standardize the analysis interval across individuals. To empirically substantiate this decision, we systematically explored whether the average MSE for both varying trial length (from noun presentation to response) and standardized trial length (for which we fixed

the trial length from noun presentation to a frame of max. 4 s for each participant) would differ in terms of individual differences (see results and analysis in the Supplementary Material S2 (https://www.frontiersin.org/articles/10.3389/fnbeh.2020.00146/full#supplementary-material) illustrating the correlation between the two options of analyzing MSE, based on variable vs. standardized trial length). Pearson correlation matrices of MSE, analyzed in four concatenated trial segments of standardized vs. varying length, indicated very high associations between the two. Thus, the rank order of individuals barely differs when estimating MSE from standardized vs. varying trial lengths. Hence, the decision can be made according to theoretical considerations. Note that we aimed to capture the complete idea generation process, and the variable length covering the whole thinking time is a more appropriate option from this theoretical point of view. Thus, for the final MSE analysis, the trial segments with variable length were concatenated for each condition and participant. The concatenated segments were further divided into four data segments to be used as indicators for the structural equation modeling (SEM). The length of the concatenated signal segments did not vary within participant and across timescales; only the resolution did. Due to progressive coarse graining (from sampling interval 4 ms at scale 1 to 80 ms at scale 20), which lies at the heart of MSE calculation, the resolution of the signal differs across timescales. But the analyzed trial length varied across individuals.

To summarize, we calculated MSE for each participant, at each channel (electrode) across multiple timescales (ranging from scale 1 to 20) in 2 (conditions)*4 data segments (for adjusting unreliability of MSE estimates and for conducting statistical inference at the level of latent variables).

3.3.9 Statistical analysis

Multiscale entropy difference tests between conditions and brain-behavior associations during the creativity task (human-rated originality scores of the generated verbs) and MSE estimates were conducted by means of SEM. SEM is a generalized linear modeling framework proposed as a combination of confirmatory factor analysis and path modeling. For an introduction to SEM, we refer to Kline (2015). SEM with latent variables has the great advantage that a measure (dependent variable) can be decomposed onto (1) the true score, (2) its method or content specificity, and (3)

its measurement error. For the present endeavor, by means of SEM, measurement error (unreliability arising due to the estimation noise of MSE across different data segments) can be accounted for, prior to inferentially testing mean differences between experimental conditions. Furthermore, the SEM approach allows directly investigating the correlation between MSE captured in different experimental conditions and their difference with behavioral outcomes. Finally, with an SEM approach, integrated measures can be used to avoid multiple testing issues. Note that a measurement model requires a minimum of four indicators for a latent variable to be identified. Therefore, MSE was computed in four different segments as described above. Calculating condition-specific latent MSE variables with four indicators (latent variable for MSE during typical and original association) will thus allow to test hypotheses at the level of latent variables, which are corrected for measurement error. More importantly, by using latent variables, we can jointly test hypotheses with respect to mean differences and individual differences. In summary, we used SEM to quantify mean and individual differences in two different conditions of creative verbal associations, and we investigated the latent level relationship between MSE measures in the two conditions to make inferences about the specificity of individual differences. Statistical analyses were performed with the R Software for Statistical Computing (R Core Team, 2018). For SEM estimation, we used the lavaan (LAtent VAriable Analysis) package by Rosseel (2012). We evaluated model fit by the following test statistics and fit indices: the chi-square fit statistic (χ^2), the comparative fit index (CFI, that should exceed 0.95 for a good fit), standardized root mean square residual (SRMR; to be lower than 0.08), and root mean square error of approximation (RMSEA to be lower than 0.08); please see Kline (2015) for more information about SEM fit.

3.4 Results

3.4.1 Descriptive Multiscale Entropy results

To illustrate mean MSE differences at the observed level between typical and original associations, we computed the grand-mean MSE across the four segments of concatenated EEG trials and participants separately for both experimental conditions, each electrode, and timescale. Figure 3.4 provides line plots with error bars of grand-mean MSE during original associations (green line) and typical (purple line) associations at six frontal representative electrodes. Error

bars represent standard errors. Note that we do not aim to conduct statistical tests at this data level, which is not adjusted for measurement error. Descriptively, differences between the two conditions occurred especially at frontal electrode sites at small (scale 1–5) and medium (scale 6–15) timescales (see line plots for further electrodes in the Supplementary Material S3; (https://www.frontiersin.org/articles/10.3389/fnbeh.2020.00146/full#supplementary-material).

These results suggest that a slightly higher complexity characterized the brain signals during production of original associations as compared with typical associations. The only statistical test conducted at this level was the one on sex differences to rule out potential confounders in the subsequent latent variable analyses. Results are provided in the Supplementary Figure S4 (https://www.frontiersin.org/articles/10.3389/fnbeh.2020.00146/full#supplementary-material), which suggest no sex differences in MSE within and between the task conditions.

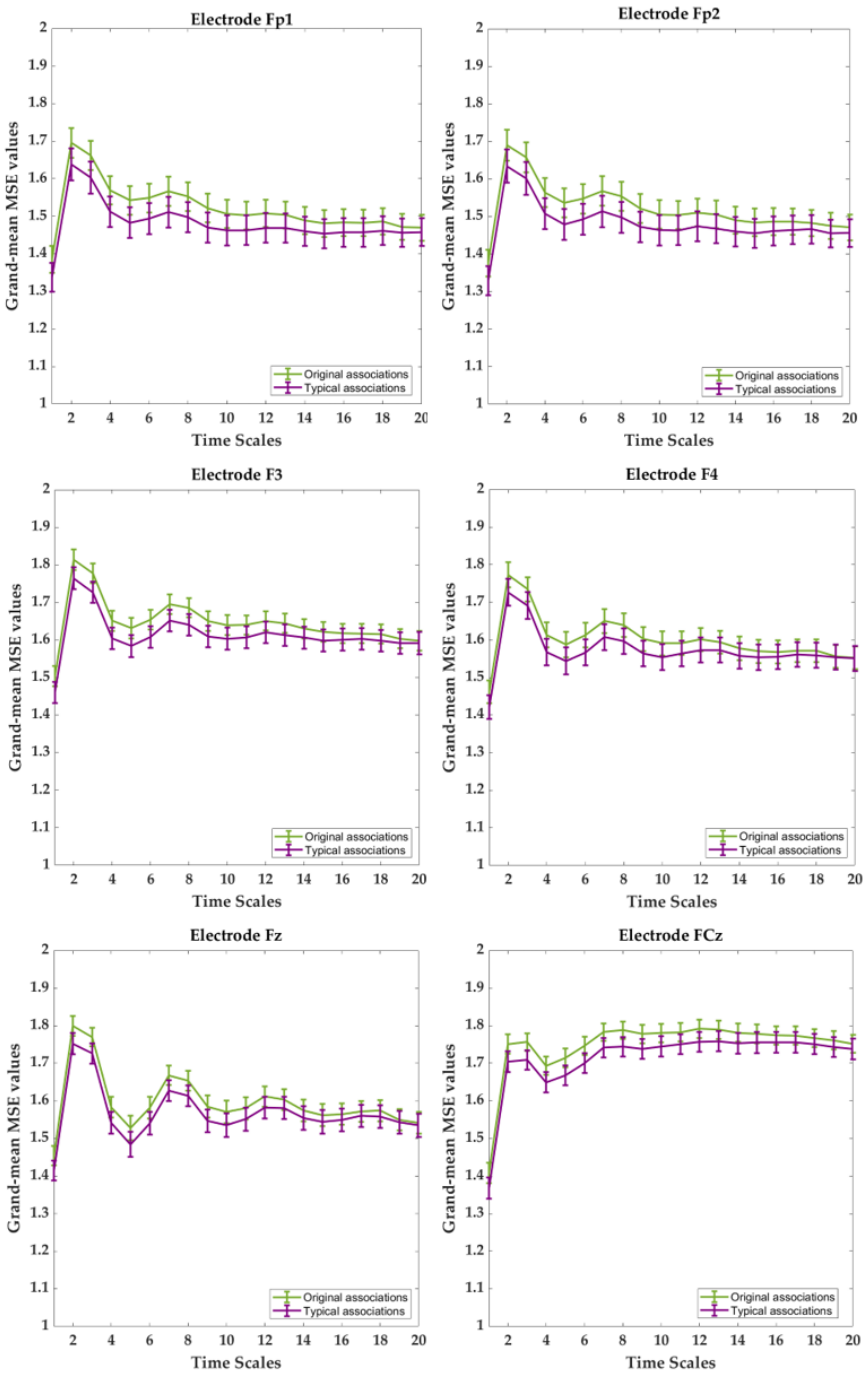

Figure 3.4. Grand-mean multiscale entropy (MSE) during typical and original associations at frontal electrodes across 20 time scales. The MSE is slightly larger in the originality condition mostly at frontal electrodes at small (1–5) and medium (6–15) time scales. Error bars represent 1 SE.

Next, we visually explored the topographical pattern of the MSE difference between the two experimental conditions at this observed data level. To this purpose, we calculated the absolute differences in mean MSE between the two conditions and obtained their scalp topographies at selected small, medium, and large timescales. Visual inspection of these plots reveals six frontal

electrodes Fp1, Fp2, F3, F4, Fz, and FCz where the positive differences in MSE were the largest and P7, P3, Pz, P4, and P8 parietal electrodes where the MSE difference was negative (see Supplementary Material S5 for the topoplots at all remaining temporal scales). According to our theoretical expectations, frontal electrodes are of special interest for statistical testing at the level of latent variables. We thus selected the six frontal electrodes for latent variable analyses. Because these differences at observed level are not adjusted for unreliability, the illustration in Figure 3.5 fulfills, similarly to the line plots in Figure 3.4, a descriptive purpose only. For subsequent statistical tests, MSE measures were spatially and temporally integrated and adjusted for measurement error. Thus, an average across these six electrodes and integrated measures across temporal scales was considered (see below).

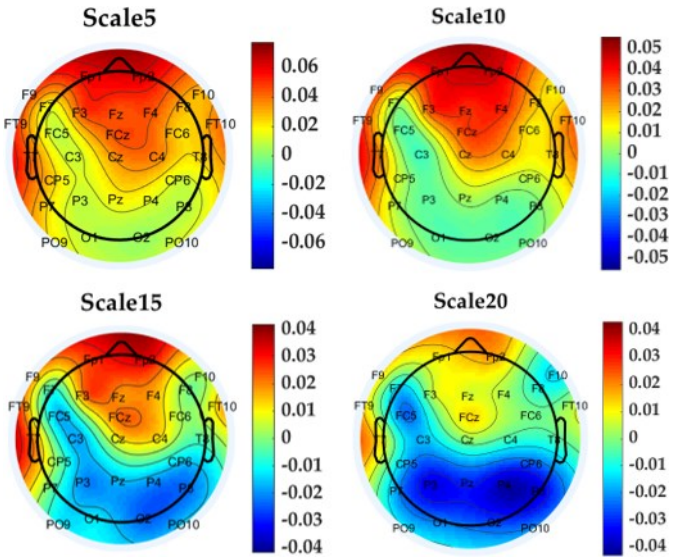

Figure 3.5. Topographic plots of grand-mean multiscale entropy (MSE) difference between original and typical associations at time scales 5, 10, 15, and 20. These distributions illustrate that the positive difference in MSE between the two idea generation conditions occurs at frontal regions and up to scale 15 and negative differences are prominent at parietal sites at Larger scales.

3.4.2 Latent mean and individual differences in Multiscale Entropy

For the purpose of hypothesis testing, we estimated a two factorial measurement model with correlated factors (see SEM description above), differentiating latent MSE variables for typical and original associations each. To avoid multiple testing, we integrated MSE values across several scales into single scores. This procedure has been previously proposed in the literature as an

approach to handle such multiple scale measurements (see Takahashi et al., 2009; Kaur et al., 2019). Hence, we used the area under the curve (AUC) as an integrated entropy score per participant. Visual inspection of the line plots of Figure 4 suggests that the MSE difference between the two experimental conditions increases across small scales (1–5) shows a rather stable condition difference at medium scales (6–15) but no difference at large scales (16–20). Therefore, we divided the timescale-specific MSE values into three categories (small-scale MSE, ranging from scales 1–5; medium-scale MSE, including scales 6–15; and large scale, MSE from scale 16–20) and integrated the person- and condition specific MSE values by summing them across those scales (see Figure 3.6 for a graphical explanation of this procedure).

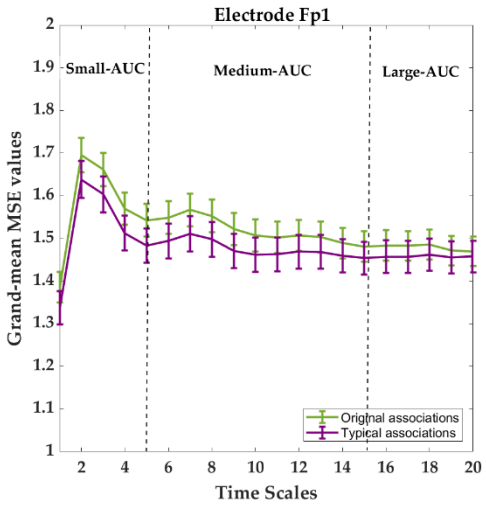

Figure 3.6. Illustration of the time scale integration using the area under the curve (AUC) measure. Small-AUC is obtained by summing up the multiscale entropy (MSE) values across time scales 1–5; Medium-AUC by integrating across scales 6–15; and Large-AUC is achieved by integrating MSE values across scales 16–20. Note that the magnitude of Medium-AUC values differs from the other two, because 10 as compared to 5 single values are summed up in that case.

With the use of these AUC scores, separate measurement models for small, medium, and large scales were estimated (Figure 3.7). Using these models, we investigated whether latent condition-specific means are substantially different from each other or can be constrained to equality without significantly diminishing model fit (according to the $\Delta\chi^2$-difference test). If the model fit would substantially decrease by constraining the latent MSE means of the typical vs. original association conditions to equality, we would conclude that the mean difference is statistically substantial.

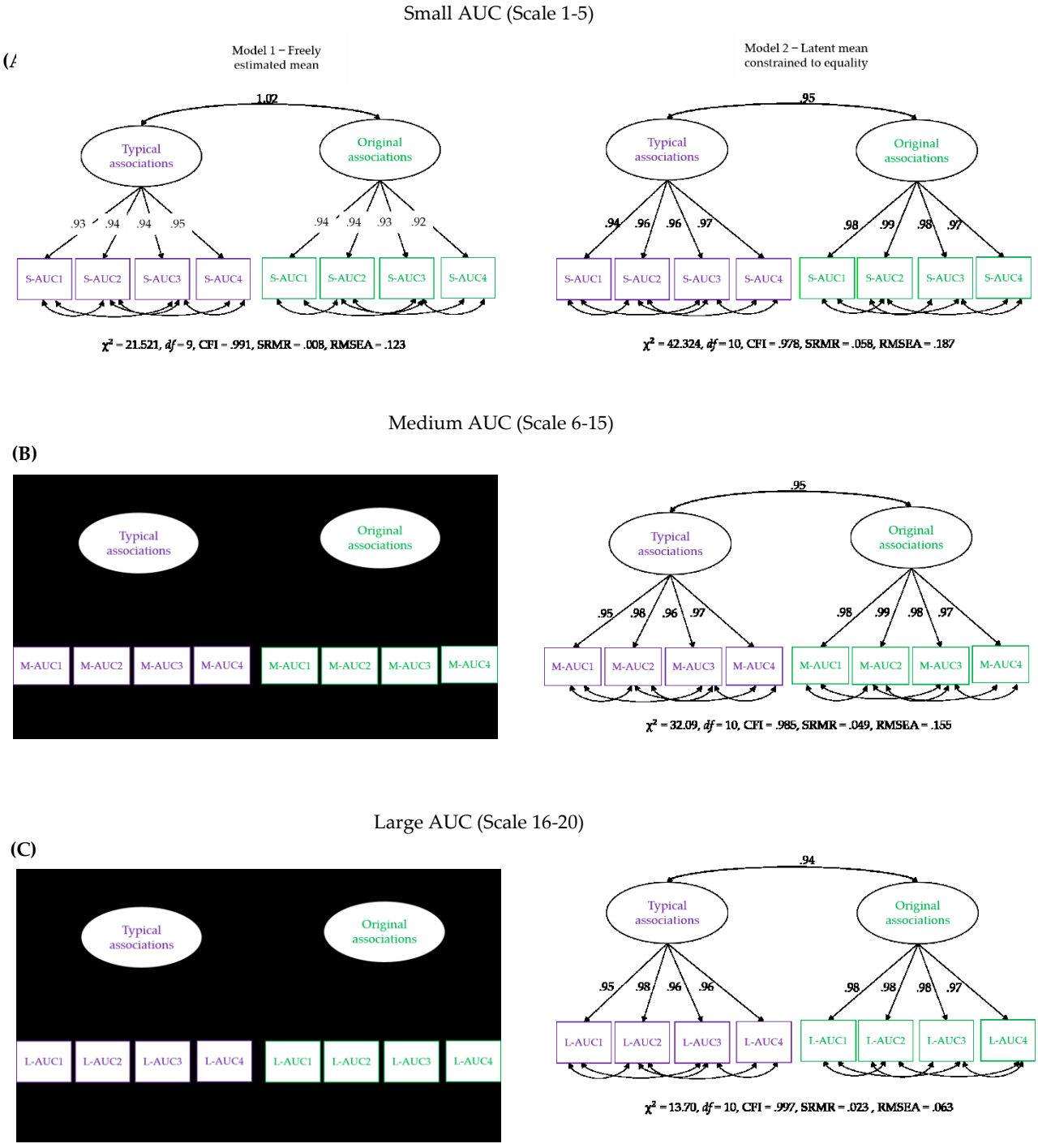

Figure 3.7. Schematic representation of measurement models investigating the difference between latent means and individual differences in multiscale entropy (MSE) as measured in typical and original associations. We estimated two models: Model 1 – in which the mean of the latent variables (typical and original associations) were freely estimated, and Model 2 – in which the means of the latent variables were fixed to equality. These models were separately estimated for (A) Small-AUC scores (integrated across smaller time scales 1–5), (B) Medium-AUC scores (integrated across medium time scales 6–15), and (C) Large-AUC scores (integrated across large 16–20 time scales). S-AUC (1–4) – first to fourth indicators of small AUC scores, M-AUC (1–4) – first to fourth indicators of medium AUC scores, L-AUC (1–4) – first to fourth indicators of large AUC scores. $\Delta\chi 2$, Chi-square; *df*, degrees of freedom; CFI, comparative fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean-square residual.

In Model 1, the mean of the latent MSE variables, i.e., typical and original associations, was freely estimated. In the Model 2, an equality constraint was set on the latent variables' means. Results are displayed in for latent variables.

Table 3.1, which shows the estimated means and the latent mean after imposing the equality constraint. For small AUC, the $\Delta\chi^2$ test showed that the equality constraint diminished the model fit significantly. For medium AUC, the model fit significantly diminished as well by constraining the means to equality, which was, however, not the case for large AUC. These results suggest that the modeled latent mean differences in MSE between the two conditions are statistically substantial for small and medium, but not for large, timescales. To provide an effect size estimate, we averaged across the indicators separately for small, medium, and large scales and used the formula for calculating the paired samples, repeated measures d coefficient. For small AUC, the observed average mean MSE during typical associations was 6.436 (*SD* = 1.207), whereas in original associations, it was 6.633 (*SD* = 1.109). Given a correlation of *r* = 0.957 between the repeated within-person measures, the effect size for small AUC amounts to *d* = 0.531.

For medium AUC, the observed average mean MSE during typical associations was 14.271 (*SD* = 2.698), whereas in original associations, it was 14.608 (*SD* = 2.477). Given the correlation of *r* = 0.954 between the repeated within-person measures, the effect size for medium AUC amounts d = 0.414. For large AUC, the observed average mean MSE during typical associations was 6.284 (*SD* = 1.171), whereas in original associations, it was 6.346 (*SD* = 1.061). Given a correlation of *r* = 0.956 between the repeated within-person measures, the effect size for large AUC amounts *d* = 0.178. The *d* coefficients indicate a moderate effect size for small and medium scales and a negligible effect at large scales. Note that we provide effect size estimates for the manifest variables, because they are more conservative and because no clear guidelines exist for calculating *d* for latent variables.

Table 3.1. Model fit indices of the nested SEMs estimating latent mean differences in MSE between typical and original associations

Time scales	Model	CFI	χ^2	df	$\Delta\chi^2$	Δdf	*p*-value	Estimated mean MSE during original associations	Estimated mean MSE during typical associations	Mean MSE with equality constraint
Small-AUC	1	0.991	21.521	9	–	–	–	6.729	6.457	6.744
	2	0.978	42.324	10	20.803	1	<.001			
Medium-AUC	1	0.995	16.534	9	–	–	–	14.73	14.21	14.769
	2	0.985	32.093	10	15.559	1	<.001			
Large-AUC	1	0.999	9.953	9	–	–	–	6.386	6.276	6.398
	2	0.997	13.7	10	3.747	1	> .05			

Note. CFI, comparative fit index; χ2, chi-square; Δχ2, chi-square difference between Model 1 (freely estimated latent means) and Model 2 (equality constraints on latent means); Δdf, difference in the degrees of freedom between Model 1 and Model 2; SEM, structural equation modeling; MSE, multiscale entropy; AUC, area under the curve.

To investigate the specificity of individual differences in MSE during typical vs. original associations, we examined the latent level correlation between the two latent variables in Figure 3.7. This is to ask whether individuals systematically differ with respect to MSE between the original and typical associations or whether the rank order of individuals is indistinguishable between the two conditions. Figure 3.7 illustrates the measurement models showing the relationship between the two latent variables for small-, medium-, and large-AUC scores. The latent level correlations are perfect (even abnormally estimated above the boundary of the correlation scale) when condition-specific means are allowed. Correlations are close to unity in each AUC (small-, medium-, and large-AUC) when latent means were constrained to equality. Given these estimates, it can be concluded that individuals exhibiting higher (or lower) MSE in original associations are also characterized by higher (or lower) MSE during typical associations. Thus, the rank order of individuals is non-distinguishable with respect to MSE in the two verbal association conditions.

3.4.3 Relationship between human-rated originality scores and the latent mean Multiscale Entropy differences between typical and original associations

To investigate how the MSE difference between typical and original associations is related with human originality ratings of the produced verb, we applied latent difference score modeling (LDSM; McArdle and Hamagami, 2001). Because observed difference scores are poor in their psychometric quality (lack of reliability and restricted variance; Raykov, 1999) and the covariance structure of the measurements is not taken into account when using them, relationships with behavioral outcomes were investigated with LDSM. LDSM parameterizes the absolute difference between two latent variables—that is, two experimental conditions in the present case. The estimated variance of the latent difference scores quantifies individual differences in condition effects. We estimated difference score models for small, medium, and large AUC and regressed them onto originality ratings of the verbs generated during production of typical vs. original associations. To test the hypotheses whether the MSE difference is larger at heightened originality values, the difference score was additionally regressed onto the squared originality ratings (quadratic effect, which was expected to be positive). Figure 3.8 schematically illustrates the difference score LDSMs, separately for small-, medium-, and large-AUC scores, including the linear terms only, because none of the quadratic effects turned out to be significant (see also Table 3.2). As illustrated in Table 3.2, individuals substantially vary in their MSE (absolute) difference scores between typical and original associations. This difference at small-scale MSE was positively associated with human-rated originality scores when original associations were expected. However, none of the further linear and quadratic associations were statistically significant.

Table 3.2: Results of the LDSM models

Model	*SD*	Intercept of difference score	Regression weight of the difference score onto human-rated originality scores in	
Small- AUC	0.26	0.25	-0.18	**0.2**
Medium-AUC	0.62	0.85	-0.19	0.1
High-AUC	0.26	0.33	-0.18	0.04

Note. Effect sizes above 0.20 are printed in bold. These models additionally included quadratic terms to test the hypotheses whether the difference between MSE in typical and original association is larger for heightened originality scores. The quadratic associations failed to reach statistical significance (regression weight of the quadratic term between human-rated originality score and the difference in MSE between typical and original association for small AUC = 0.024, p = 0.8; medium AUC = 0.009, p = 0.9; and large AUC = 0.008, p = 0.9). LDSM, latent difference score modeling; AUC, area under the curve; MSE, multiscale entropy.

Because the MSE difference between the two conditions was negative at parietal electrodes, we additionally performed statistical tests [the same as for frontal region of interests (ROIs)] for the parietal electrodes (P7, P3, Pz, P4, and P8). Note that these effects were not hypothesized. These exploratory analyses revealed no statistically substantial associations (see results in the Supplementary Material S6).

Thus, the present data, given the statistical power at hand, reveals no robust linear association between the MSE difference between typical and original association conditions and human-rated originality scores of the produced associations. However, with a larger sample size, we might find that individuals with higher temporal complexity in frontal sites when producing original associations tend to be more original.

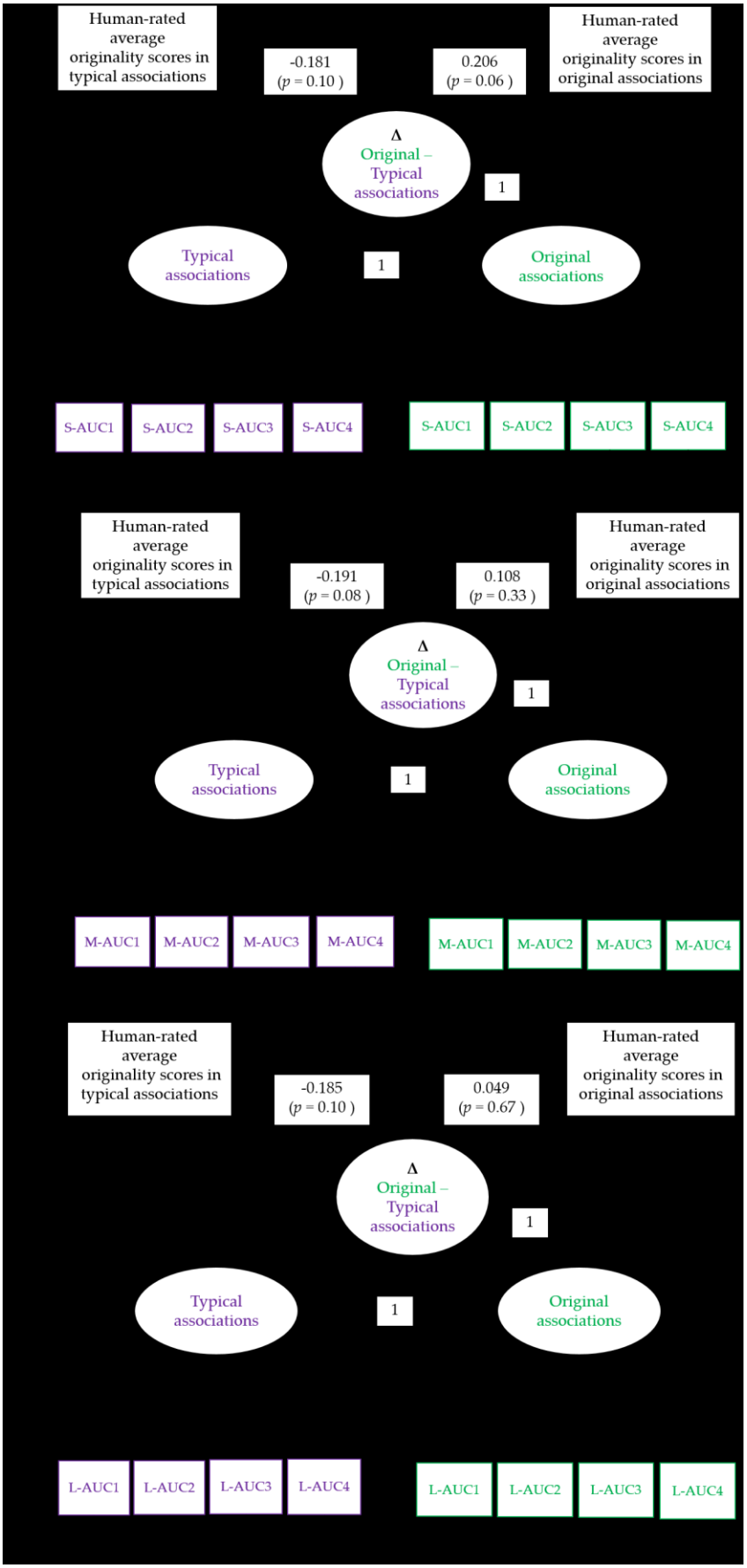
Human-rated average originality scores in typical associations
-0.181 (p = 0.10)
0.206 (p = 0.06)
Human-rated average originality scores in original associations
Δ Original – Typical associations
1
Typical associations
1
Original associations
S-AUC1
S-AUC2
S-AUC3
S-AUC4
S-AUC1
S-AUC2
S-AUC3
S-AUC4
Human-rated average originality scores in typical associations
-0.191 (p = 0.08)
0.108 (p = 0.33)
Human-rated average originality scores in original associations
Δ Original – Typical associations
1
Typical associations
1
Original associations
M-AUC1
M-AUC2
M-AUC3
M-AUC4
M-AUC1
M-AUC2
M-AUC3
M-AUC4
Human-rated average originality scores in typical associations
-0.185 (p = 0.10)
0.049 (p = 0.67)
Human-rated average originality scores in original associations
Δ Original – Typical associations
1
Typical associations
1
Original associations
L-AUC1
L-AUC2
L-AUC3
L-AUC4
L-AUC1
L-AUC2
L-AUC3
L-AUC4

Figure 3.8. Simplified illustration of the latent difference score models (LDSMs) estimated for (A) small-AUC, (B) medium-AUC, and (C) large-AUC values of multiscale entropy (MSE). Typical and original associations are latent MSE variables indicated by four AUC values. Human-rated cross-trial average originality scores are obtained during the production of typical and original associations in the Verb generation task. 1 Original-Typical association is the MSE difference score between the experimental conditions. S-AUC1-4, M-AUC1-4, and L-AUC1-4 are the first to fourth AUC indicators of the MSE values for small, medium, and large time scales, respectively.

3.5 Discussion

The present study aimed to understand creative verbal association states at the neural level within the framework of complexity theories. We employed the MSE algorithm as a complexity estimate in neural signal during a verb generation task. As hypothesized, temporal complexity was higher during production of original associations as compared with typical verbal associations across small and medium timescales in frontal areas. However, the magnitude of this difference was small or moderate and statistically substantial only up to scale 15 (in the range of medium scales). The latent correlations between entropy as estimated in original vs. typical verbal association states revealed that the two measures are isomorphic with respect to individual differences. Furthermore, the relationship between human-rated originality scores in typical association condition and the entropy difference between original and typical association states is small and negative, but statistically not significant. A significant negative correlation would suggest that individuals with a larger MSE difference make less original associations when this is their task. However, the relationship of the MSE difference with originality scores in the original association condition was positive. This means that individuals who show a larger difference in small-scale entropy between the original and typical associations are better able to conform to the requirements of both tasks. These associations, however, need further investigation because none of these correlations could be robustly established with the data at hand. Taken together, we report results that are partly in line with the hypothesis that BSC is a sensitive neural marker of creative verbal association generation.

Higher entropy during original association production as compared with typical associations shows that signal complexity is a sensitive average marker of verbal creativity. This means that brain activity tends to become more complex in average when producing original verbal associations. This main finding can be considered a step ahead to establish brain complexity as a

correlate of creative verbal associations. It goes beyond previous studies that solely associated resting BSC as a trait measure with creativity task performance. For example, Ueno et al. (2015) found that more creative elderly individuals exhibited higher MSE measured in resting-state EEG. To our best knowledge, only the study by Rominger et al. (2019) examined creative idea production as reflected in EEG signals during a creative task (figural DT) and showed increased functional coupling of brain networks from idea generation to idea elaboration. Complementing these previous studies, the present study is a further step toward an elaborated neural complexity theory of creativity.

Since both brain oscillations and MSE characterize the dynamical features of a time series, one may wonder what the conceptual differences between these two measures are. And how do they differentially reflect the functional characteristics of the brain? Some studies have related creativity with neural oscillations (for a review, see Fink and Benedek, 2014). Neural oscillations also provide critical information about neural dynamics. For example, slow neural oscillations reflect mechanisms that support information integration and communication between large-scale neural networks (Cohen, 2014). Thus, oscillation measures (e.g., power spectra of different frequency bands) are also suitable for studying brain activities over multiple spatiotemporal scales. However, conceptually, oscillation measures are different from MSE measures. By definition, oscillation reflects the predictable feature of the dynamics and may be too simple when high level cognition like creativity is concerned. Following the Honing theory, creativity is assumed to be associated with higher psychological entropic states, characterized by largescale functional and connectivity patterns reflecting complex dynamical interacting systems (Zabelina and Andrews-Hanna, 2016; Beaty et al., 2018). Therefore, we need a suitable method to identify this entropic state and parameterize the complexity over multiple timescales. As elaborated when introducing the MSE algorithm, small and medium MSE timescales reflect fast and local neural dynamic activities, and large scales are concerned with slow dynamics across broader spatial scales. On this account, we propose that MSE is a conceptually more suitable measure to parameterize the complexity of creative brain activity.

As predicted, the higher complexity during original associations was highest in frontal regions. Our results thus add up to the knowledge on the involvement of frontal areas during creative

tasks. For example, Dietrich and Kanso (2010) summarized the literature according to which vast areas of the PFC are consistently involved during performance on different creativity tasks. Further empirical evidence has also revealed an active anterior PFC, especially during creative idea generation, musical improvisation, analogical reasoning, and metaphor processing (Abraham, 2018).

With this study, we aimed to go beyond mean differences findings by additionally demonstrating specific rank orders of individuals in less vs. more creative brain states. However, we found no specificity. This means that entropy is quantitatively higher during original verbal production as compared with typical verbal production, but it does not differentiate individuals depending on their brain states. Thus, there is a shift in mean MSE depending on the brain state, but individual differences in MSE remain stable across states. A possible explanation for the non-expected perfect rank order stability finding can be that both cues (original and typical associations) tap into the lexical system, where as a consequence of activating a concept (by the noun) an associated word (the verb) is produced. If an individual has a rich lexicon, she/he will be able to produce highly original verbs (semantically distant or indirectly associated with the noun) relying on the same entropic brain state needed to activate the most conventional associations. In these individuals, the difference in entropy between the two conditions might be larger than in individuals with a poor lexicon, who will be less able to find original as well as typical associations.

Another potential explanation of these findings is that MSE might not be sensitive enough to differentiate the closely coupled dimensions of creative ability—theoretically typical verbal production being considered as the fluency facet of creativity. Therefore, during an attempt to produce original associations over several seconds, these closely related facets of creative ability should probably be rapidly shifting back and forth. Because MSE analysis integrates over larger time intervals, i.e., several seconds that leads to low time resolution, such brief creative states (producing typical and original associations) in the brain become inseparable when such larger swaths of time are considered.

3.6 Future directions

The current findings are limited to a word production task that taps into one aspect of creativity, i.e., verbal creativity. Future studies focusing on individual differences in creativity will need to employ task(s) that can capture multiple aspects of creativity (i.e., fluency, flexibility, and originality, also in figural and numerical domains). A new line of creativity studies recently proposed a neurocognitive framework of creative cognition that should be characterized as an interplay between memory, attention, and cognitive control (Benedek and Fink, 2019). In addition, resting-state functional connectivity in cognitive control networks has been shown to be associated with creativity (Beaty et al., 2014, 2018; Sun et al., 2019). Therefore, in future complexity studies on creative cognition, it will be critical to co-examine specific cognitive functions elementary to creative cognition. Thus, a larger psychometric task battery including cognitive control, working memory, verbal knowledge tasks, and resting-state brain activity would increase sophisticated understanding of creative brain states in terms of individual differences. Furthermore, recently proposed methods for explicit identification of multivariate patterns in neural data (Haxby et al., 2001; Fahrenfort et al., 2018) could be combined with entropy estimates in the future. The aim would be to measure the transition among the identified multivariate patterns as a potential marker to quantify the spatiotemporal switching of the dynamical patterns, which may allow better differentiating creative vs. less-creative states. Because MSE captures complexity across different temporal scales only, it can just implicitly reflect the spatiotemporal interactions in the underlying neural systems (Liu et al., 2019). In summary, future studies might successfully combine modern brain signal analysis methods with multivariate modeling of brain-behavior associations to better understand individual differences in verbal creativity.

3.7 Ethics statement

The studies involving human participants were reviewed and approved by the ethics committee of the Department of Psychology, Humboldt-Universität zu Berlin (approval number 2012-46). The patients/participants provided their written informed consent to participate in this study.

3.8 Author contributions

YK and AH conceptualized the study. YK designed it, collected the data, which she independently preprocessed and analyzed, discussed results with all co-authors, and drafted the manuscript. AH and WS supervised the task design and the EEG data acquisition, processing and statistical analysis, and results interpretation and theoretical discussion. GO and CZ supervised the MSE analysis and contributed to the interpretation of results. SW contributed to the behavioral data collection and analysis. All co-authors were involved in the editing of the manuscript at several stages.

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4 A neural signal complexity perspective on the relationship between creativity, intelligence, and cognitive control

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4.1 Abstract

Functional connectivity studies demonstrated that creative idea generation builds upon an interplay of multiple neural networks involving the cognitive control system. Theoretically, cognitive control has been discussed as the common cognitive basis underlying the positive relationship between creativity and intelligence. However, we still lack a detailed investigation of the association patterns between cognitive control and multiple facets of creativity measured by divergent thinking (DT) tasks (i.e., fluency and originality) and intelligence (i.e., fluid and crystallized intelligence). In the present study, we examined these relationships at the behavioral and the neural level based on $N = 77$ young adults. We focused on brain signal complexity (BSC), parameterized by Multi-Scale Entropy (MSE) measured during verbal DT and a cognitive control task. We demonstrated that MSE is a sensitive neural indicator of originality as well as inhibition. Then, we examined MSE relation-ships with facets of creativity and intelligence. In a series of across-scalp analyses, we show that overall MSE measured during DT is most robustly associated with facets of creativity, whereas MSE measured during cognitive control is not only associated with such, but also with fluid and crystallized intelligence. The present explorative study broadens our understanding of the relationship between creativity, intelligence, and cognitive control from the perspective of temporal brain signal complexity and it has the potential to inspire future BSC related theories of human creativity.

4.2 Introduction

Creativity and intelligence are vital cognitive abilities to human endeavor, evolution, and cultural transformation (Gabora & Kaufman, 2010). Current empirical evidence supports that these two mental faculties are positively associated. However, the mechanism underlying this association is still being explored through the lens of psychometric and neuroscientific investigations. A proposed explanatory mechanism of the relationship between creativity and intelligence poses a shared and differential involvement of inhibitory control in both abilities (Benedek et al., 2014). An increasing body of research converges on the notion that inhibition is required for creative idea generation as individuals need to inhibit the typical and dominant responses to produce unique, creative ideas. Thus, inhibitory control is necessary to restrain usual

responses, fostering creative idea generation (see Cassotti et al., 2016 for a review). Network neuroscience and latent variable analysis of multiple behavioral performance measures have investigated the mechanisms underlying the creativity–intelligence relationship (Beaty et al., 2016; Kenett & Faust, 2019), but hitherto applied functional connectivity measures on Magnetic Resonance Imaging (MRI) data ignore the temporal patterns in neural activities.

Temporal complexity measures of brain signals yield explicative information about the functional activity of neural networks during resting and task processing states. Studies have demonstrated Brain Signal Complexity (BSC) to be a sensitive neural marker of creative idea generation (Kaur et al., 2020; Ueno et al., 2015), healthy brain functioning, knowledge representation (Heisz et al., 2012), cognitive control (Grundy et al., 2019; Wang et al., 2020), and cognitive performance in general (for a review see Garrett et al., 2013). Nevertheless, it remains to be explored how BSC measures that were captured during different tasks are associated with each other, especially with respect to the creative and inhibition-related neural states. Furthermore, the question remains on how BSC in these states is related with ability facets of creativity and intelligence. Therefore, in the present investigation, we explore the relationship between creativity (including fluency and originality as facets), intelligence (fluid and crystallized), and cognitive control (inhibition) at the behavioral and neural level.

4.2.1 On the association between creativity and intelligence – behavioral and neural evidence

A series of behavioral and neurocognitive studies demonstrated a positive relationship between creativity and intelligence (e.g., Benedek et al., 2014; Silvia, 2008, 2015). With respect to the behavioral level, considerable efforts have been made to link creativity with general intelligence (g), for example as a lower-order factor of g underneath general retrieval ability (McGrew, 2009), but also specifically with fluid (gf) and crystallized intelligence (gc; e.g., Weiss et al. 2020). For example, robust positive associations between gc and creativity (Howrigan & MacDonald, 2008; Krumm et al., 2018), and gf and creativity (e.g., Benedek et al., 2014) were demonstrated. A recent, fairly large and multivariate study by Weiss et al. (2020) revealed moderate positive latent level relationships between divergent thinking (DT), g, and gc. The

findings replicated the earlier studies on the association between DT and gc (Beaty & Silvia, 2012; Silvia & Beaty, 2012), suggesting that verbal creativity benefits from the richness of verbal knowledge available to the individuals. Studies also demonstrated the association between DT and gf (Beaty & Silvia, 2012; Bendek et al., 2012, 2014; Silvia & Beaty, 2012). Jauk et al. (2013) provided further support for the notion that intelligence is required to put creative idea generation into action (Sternberg and O'Hara 1999).

Network neuroscience revealed considerable overlap between brain networks associated with individual differences in creativity and g. The functional network connectivity underlying creative idea generation is characterized by interactions between two crucial neural networks: The default mode network (DMN) and the executive control network (ECN). The former consists of a set of midline and inferior parietal regions considered to facilitate the self-referential thought process, introspection, and imagination, whereas the latter consists of lateral prefrontal and anterior inferior parietal regions underlying externally focused attention and inhibitory control (Beaty et al., 2015, 2016). The dynamics of these two networks were demonstrated to be associated with intelligence. For example, a resting-state functional connectivity study by Hearne et al. (2016) showed greater connectivity between the DMN and the fronto-parietal network (FPN) to correlate with higher intelligence scores. The FPN involves hubs instantiating cognitive control which serves to initiate new task states by flexibly interacting with other brain networks (Marek and Dosenbach 2018). A study by Cole et al. (2015) found that across-network connectivity of the lateral prefrontal cortex (a hub of the FPN) predicted gf ability.

Although the DMN and ECN operate in opposition, their coordination during heighted creativity and reasoning can be considered a consistent finding in network neuroscience of creativity and reasoning (Beaty et al., 2015, 2016, 2019; Hearne et al., 2015, 2016). As further support, a me-ta-analysis conducted by Santarnecchi et al. (2017) highlighted the interaction between the attention, salience, and cognitive control networks to serve gf. Associations were also demonstrated for structural connectivity networks. A recent diffusion tensor imaging study by Kenett et al. (2018) examined the extent and ways in which cognitive control contributes to creativity and intelligence. The authors demonstrated that DT was associated with modal

controllability within regions of the DMN-ECN network. Modal controllability characterizes brain regions that require substantial input energy. However, better gf was related with average controllability which characterizes brain regions that require less input energy. Thus, the authors refer to creativity as being a "difficult-to-reach" neural state and gf as an "easy-to-reach" neural state. Overall, DT and gf were associated with network controllability of regions within the DMN-ECN network, demonstrating multiple control processes to be involved in creativity and intelligence. These results are consistent with previous studies which demonstrated a substantial role of the DMN-ECN interaction in creativity, as well as gf (Beaty et al., 2015, 2016; Hearne et al. 2015, 2016). Furthermore, the results converge with the abundant literature pointing to the involvement of the prefrontal cortex (PFC) in creative thinking (see Dietrich and Kanso 2010 for a review), suggesting that the dynamic modulation of cognitive control, driven by PFC networks, is potentially the key mechanism underlying creative idea generation (Chrysikou et al., 2018; Dietrich 2004).

4.2.2 On the role of cognitive control in creativity and the creativity-intelligence relationship

Cognitive control is the process by which automatic responses are inhibited and flexibly adapted to produce complex goal-directed thoughts (Morton et al., 2010). It encompasses multiple facets, one of which is inhibition, the process which guards the cognitive system against salient but irrelevant stimuli (Jones et al., 2016). Thus, the ability to inhibit an internal tendency, or to restrain from external information is generally referred to as inhibition ability (Xie et al., 2017). The strongest argument linking cognitive control and creativity is related to inhibitory control. The following working mechanism has been proposed: The inhibition of common ideas and the later evaluation and monitoring of produced responses lead to improved creative idea generation (Beaty et al., 2014; Nusbaum et al., 2014; Nusbaum and Silvia 2011). Thus, individuals need to inhibit irrelevant or common responses to create novel ideas (Benedek et al., 2012; Camarda et al., 2018; Zabelina and Ganis 2018).

Another line of theoretical argumentation proposes that the cognitive basis of creativity rather relies on the joint contributions of associative and executive abilities. For example, a study by

Beaty et al. (2014) explored how associative and executive processes relate to creativity. To this aim, the study measured the semantic distance of responses generated during verbal fluency tasks, broad retrieval ability, and gf. By means of structural equation modeling (SEM), the authors showed that associative abilities indicated by semantic distance and individual differences in broad retrieval ability and gf predicted DT ability. Moreover, cognitive control has been shown to partly explain the creativity-intelligence relationship. By using a latent variable modeling approach, Benedek et al. (2014) examined whether inhibition, updating, and shifting would explain the relationship between the originality facet of creativity and gf. They showed that gf was significantly associated with updating, but not with shifting and inhibition. Creativity was predicted by updating and inhibition, but not by shifting. Furthermore, the study revealed that accounting for these executive functions in gf and creativity diminished the association between the two. In a similar line of research, an even earlier study by Nusbaum and Silvia (2011) showed that the effect of gf on DT was mediated by switching.

To conclude, there is considerable empirical evidence showing that certain executive functions (inhibition and updating) are indeed critical to generate creative thoughts (Diamond, 2013), and they also seem to play an explanatory role in the creativity-intelligence relationship. The aforementioned role of cognitive control demonstrated at the behavioral level delivers an explanation for the involvement of an extensive network of brain regions such as the DMN and ECN, and local PFC networks in cognitive control (see above). These widely distributed and local networks serving creativity seem to encompass two contradictory neurocognitive states. An interpretation of their simultaneous engagement during creative ideation has been offered in a recent review by Chrysikou (2018). It emphasized the importance of bottom-up and top-down processes involved in creative idea generation. The former processes rely on the activity of the DMN and contribute to making un-anticipated conceptual associations relevant for the idea generation phase. The latter processes rely on the PFC and retain the evaluation of significance, feasibility, viability, and efficacy of the produced associations along the bottom-up loop. Thus, there seems to be an iterative switching between bottom-up or spontaneous and top-down or controlled processing steps argued to be essential for creative thinking.

4.2.3 Brain Signal Complexity (BSC) as a neural marker of creativity and intelligence

Brain signal complexity (BSC) arises from the interaction of numerous neuronal circuits which operate over a wide range of temporal and spatial scales. These spatio-temporal fluctuations reveal important underlying dynamical information of the brain. This is to say that the inherent properties of a complex system are manifested in the features of the signals produced by it (McDonough and Nashiro 2014; Ueno et al., 2015). Therefore, an understanding of complex fluctuations of neural signals can capture essential underlying features describing the functioning of the system. The analysis of the underlying complexity of EEG signals has been argued to provide powerful insights into human brain functioning. BSC has been previously studied by means of entropy-based methods which quantify the complexity, uncertainty, or irregularity of a complex system's activity (Sandler, 2017), such as the brain. Thus, entropy-based methods are well-suited concepts to estimate neural signal complexity. Multi-Scale Entropy (MSE; Costa et al., 2002, 2005) provides temporal complexity estimates over a range of multiple spatio-temporal scales. These temporal scales are broadly divided into small and large scales when interpreting complexity measures. Complexity at small temporal scales informs about local neural processing and characterizes the irregularity of the high-frequency dynamics, whereas large temporal scales are considered to represent joint activity across more widely distributed networks and characterize low-frequency dynamics (Courtiol et al., 2016). Thus, taking different scale levels together, MSE estimates reveal the relative contributions of local and global information processing in the brain (Grundy et al., 2017; McIntosh et al., 2014; Vakorin et al., 2011).

Several studies have estimated BSC by means of MSE and demonstrated that it is a neural marker of healthy brain functioning, cognitive performance, typical development, and knowledge representation, etc. (Garrett et al., 2010, 2013; Heisz et al., 2012; Lippé et al., 2009; McIntosh et al., 2008; Mišić et al., 2010). Hence, MSE is a well-established neural complexity measure and a neural marker of cognition. MSE of temporally and spatially distributed brain activity (as measured by EEG or fMRI) acquired during resting or task performance states have been also related with individual differences in creativity and intelligence, however in separate studies. For example, a study by Ueno et al. (2015) showed higher MSE in resting-state EEG across large temporal scales

in more creative as compared with less creative elderly individuals. A resting-state fMRI study by Shi et al. (2019) showed regional brain signal entropy to be positively correlated with DT. Furthermore, the authors pointed out that creativity was closely related to the functional dynamics of the cognitive control network involved in cognitive flexibility and inhibition. Moreover, brain signal entropy in resting-state fMRI showed substantial associations gc (Saxe et al., 2018) and information from cortical entropy profiles effectively predicted several cognitive abilities (Liu et al., 2020).

In a recent study of us using parts of the data also analyzed here (Kaur et al., 2020), we showed that BSC, as indexed by MSE, was higher in neural states in which individuals were asked to produce unusual, creative as compared to usual, fluent verbal associations. This was the first evidence for BSC to prove as a neural state marker of creative verbal associations. Based on the above literature and our previous finding we thus infer that creativity, gf, and gc are all associated with neural complexity to some extent. But how much are these associations distinct and which cognitive states contribute to their distinction? Can BSC measured during cognitive control explain the fact that BSC was discovered to be a neural marker of creativity, but also of reasoning? Can neural complexity provide insights about the associations between gf, gc, fluency, and originality? Given the theorized role of cognitive control in creativity and the creativity-intelligence relationship, we expect MSE in cognitive control brain states to provide further explanations.

4.2.4 Aims of the study

In line with the above-outlined evidence, we suggest that the relationship between creativity, intelligence, and cognitive control is due to task-dependent synchronized co-activation of several local and largely distributed brain networks, including the FPN, DMN, ECN, and the salience network (SN). Thus, in line with the literature, we argue that the investigation of the interrelations between these complex mental abilities and their underlying neural mechanisms needs to also rely on methods capturing temporal neural complexity characterizing those brain networks. MSE is thus, a candidate measure because it captures neural complexity across local and wide-spread neural networks. Investigating individual differences in the EEG-derived MSE and behavioral

performance outcomes indicating creativity, intelligence, and cognitive control, as well as their relationship, will thus provide new and complementary insights into the neural foundations of the creativity-intelligence relationship. To date, there is no study that directly examined the relationship between MSE measured during creativity and cognitive control tasks. Furthermore, given the notion that cognitive control partly explains the relationship between creativity and intelligence, it remains to be investigated whether MSE captured during verbal creativity and inhibition are differentially associated with behavioral outcomes of gf, gc, and DT tasks, measuring fluency and originality.

For this study, we acquired behavioral measures of gf, gc, fluency, originality, and inhibition, as well as brain signals derived from the EEG during the performance on a verbal DT (creativity measure) task and a cognitive control (inhibition measure) task. The verbal DT task required participants to produce unusual or creative and fluent or typical verbal associations. We also label MSE during creative verbal association production as MSE in creative idea generation and MSE during typical verbal association production as MSE in fluent idea generation. The cognitive control task consisted of inhibition (i.e., high control states) and non-inhibition (i.e., low control states) conditions. Generally, in line with Benedek et al. (2013), we expect that inhibition would partly account for the creativity-intelligence relationship at the behavioral level. Further, our previous study (Kaur et al., 2020) has shown that the MSE in different task conditions of verbal creativity (i.e., during productions of original vs. typical associations in a verbal DT task) were different on average but highly correlated. However, different task types (e.g., creativity vs. inhibition) involve different mental operations, and signal complexity during such task states are expected to have weaker relationships. We expect that individual differences in MSE measured during the production of creative verbal associations are more strongly associated with MSE during inhibition as compared with the associations between inhibition MSE and MSE measured during typical association production. This is because theoretically, the generation of original associations implies inhibiting usual associations (see above). However, also fluency implies inhibiting incorrect association, thus a relationship between MSE in inhibition and MSE for the usual association is expected as well.

Furthermore, we aim to explore the relationships between MSE indicators of creativity and cognitive control with gf, gc, fluency, and originality performance, measured with independent behavioral tasks. We also explore how the difference between MSE in original vs. typical verbal association production and MSE in inhibition vs. non-inhibition correlate with behavioral gf, gc, fluency, and originality measures. Taken all the above together in this exploratory study, we aspire to answer the following research questions:

1) Does the ability to inhibit irrelevant information explain the relationship between facets of creativity (fluency and originality) and intelligence (gf and gc)? Previous research reviewed above suggested that this is the case for originality and gf. Here we aim to extend these findings by considering multiple facets of intelligence and creativity, thus including also fluency and gc.
2) Does the grand-mean MSE measured in different conditions of cognitive control, such as high (inhibition) and low (non-inhibition) control states, differ at different time scales? This is to ask whether MSE can be in general considered a neural marker of inhibition, which is a prerequisite for investigating MSE in inhibitory brain states as a correlate of fluency and originality.
3) How is MSE captured during verbal DT task associated with MSE measured during inhibition? Is this association stronger for MSE during creative verbal association production as compared with the production of typical associations?
4) How is MSE acquired during inhibitory neural states and creative thinking associated with individual differences in gf, gc, fluency, and originality measured with multiple independent behavioral tasks?
5) Are difference scores between MSE in inhibition vs. non-inhibition, as well as fluent vs. creative idea generation more sensitive neural markers of creativity and inhibition as compared with the MSE measured during original associations vs. inhibition task trials? This is to ask whether difference scores – despite their psychometric disadvantage of variance restriction (e.g., Rogosa and Willett 1983) – are more strongly associated with behavioral gf, gc, fluency, and originality as compared to MSE simply measured in the respective task condition.

4.3 Materials and methods

4.3.1 Sample and procedure

The measurements applied in the present study were approved by the ethics committee of the Department of Psychology, Humboldt-Universität zu Berlin. Participants signed informed consent before participating in the experiments. Data were assessed in two independent sessions: 1) behavioral tasks session, 2) EEG recording session. In the first session, we acquired behavioral estimates of gf, gc, fluency, and originality from n = 159 participants. In the second session, the same participants performed two different tasks while the EEG was recorded. There was a verbal DT task (completed by n = 101) and a numerical Simon task (completed by n = 90), which were both involved in the MSE analyses. All tasks applied in both sessions were programmed with PsychoPy (Peirce and MacAskill 2018). To test brain-behavior relationships, the datasets collected during the behavioral and the EEG sessions were merged. Participants with less than 10 years of German language speaking experience were excluded. After the exclusion and given the samples available for the different measurements, the final sample included N = 77 young adults (34 females, Mage = 23.80 years, SDage = 3.79, range = 18-32). Among them, 5 had not obtained high school degrees, 58 had high school or equivalent degrees, and 14 had academic degrees (e.g., Bachelors, Masters or Diploma). The dataset and related results of the current study are available online via OSF (https://osf.io/sg9e2/).

4.3.2 Tasks performed in behavioral session

4.3.2.1 Measures of divergent thinking: Fluency and originality

We used four measures of verbal fluency and two measures of verbal originality. The two measures of verbal fluency were adapted from the verbal creativity test (Verbaler Kreativitäts-Test−VKT; Schoppe 1975), namely similar attributes (SA; e.g., "Name as many things that are inedible for humans") and inventing names (IN; e.g., "Invent as many names for the abbreviation: 'T-E-F' "). SA and IN tasks required participants to produce as many as possible context-appropriate answers within 60 seconds. The SA task consisted six and the IN task consisted 18 items. The third measure was retrieval fluency (RF; e.g., "Name as many things as possible

suitable to the given category") which was adapted from the Kit of Factor-Referenced Cognitive Tests (Ekstrom et al. 1976) and was translated from English to German language. Further, we adapted four figural fluency (FF) tasks from the Berliner Intelligenzstruktur-Test für Jugendliche: Begabungs- und Hochbegabungsdiagnostik (Berlin Structure-of-Intelligence test for Youth: Diagnosis of Talents and Giftedness; Jäger et al. 2006). This series of tasks required participants to draw objects (using paper and pencil) based on different shapes (e.g., "Draw as many shapes as possible from a given rectangle and circle") and to come up with a creative figural emblem or logo for a company. The four tasks lasted for 1:50, 3, 1:45, and 3 minutes respectively.

Verbal originality was assessed using two tasks namely combining objects (CO; e.g., "Combine two objects to build a door stopper in your house"), and nicknames (NI; e.g., "Invent a nickname for a shirt"). For each of the tasks, participants were instructed to provide a single answer that was unique and original. CO was adapted from the Kit of Factor-Referenced Cognitive Tests (Ekstrom et al., 1976) and consisted of 12 items (with a time limit of 60 seconds per item, translated from English to the German language). NI was adapted from the VKT (Schoppe, 1975) which included 9 items with a time limit of 30 seconds for each item.

4.3.2.2 Measures of intelligence: Fluid (gf) and crystallized intelligence (gc)

Intelligence was assessed in the figural and verbal content domains. We adapted three reasoning tasks from the Berlin Test of Fluid and Crystallized Intelligence (BEFKI; Wilhelm et al. 2014). The verbal part of fluid intelligence (gfv) consisted 16 items that required participants to answer questions based on relational reasoning (e.g., "If Frank is bigger than Hans. Who is the smaller of the two?"). The figural part (gff) required participants to assess how a sequence of geometric drawings created based on different rules should continue. Both of these tasks had a time limit of 14 minutes each. The crystallized intelligence (gc) tasks assessed knowledge from three broad domains: natural sciences (gcnature), humanities (gchuman), and social studies (gcsocial) using a 32 items test that lasted for 10 minutes. Further, gc items were parceled according to their domain to be used for statistical analyses.

4.3.3 Tasks performed in the EEG recording session

The recording of the EEG datasets during the performance on a verbal DT and a numerical Simon task took place in a closed, quiet, and well-illuminated room and by using the Brain Vision Recorder software (Brain Products, Germany). We used BrainAmp DC amplifiers (Brain Products, Germany) to amplify the EEG signals with an amplitude resolution of 0.1 μV at a sampling rate of 250 Hz. Cutoff filters were 0.16 and 1000 Hz at the low and high range, respectively. An EEG cap (Easycap, Brain Products, Germany) was mounted with 30 Ag/AgCl electrodes, placed according to the 10-20 system. Eye movements and blinks were monitored with electrodes positioned at the outer canthi of both eyes and below the right eye. The A1 electrode (left mastoid) was used as a reference, and AFz served as ground. Impedances were kept below 5 kΩ.

4.3.3.1 Verbal divergent thinking task

To assess verbal creativity, we used the original verb generation task (adapted from Prabhakaran et al. 2014) which was modified by translating the stimulus material into German language (for task paradigm and further details, see Kaur et al. 2020). The task required participants to produce a verb that is semantically related to the presented noun stimulus. The nouns were cued to two types of color: purple and green, in total there were 35 purple cued nouns and 32 green cued nouns. To purple cued nouns participants were expected to produce usual or typical associations – we thus instructed them to type in the verb that first came to their mind when being presented with the noun (fluency condition). To green cued nouns participants should produce original, unique verb associations in response to the noun (originality condition). In the following, we label the two conditions as 'typical associations' and 'original associations'. The task began with verbal instructions followed by an example trial and five practice trials. Participants were instructed to type in only one associated verb for each presented noun. The onset of the stimulus and the onset of the participant's typing response were time-marked, to be taken as signals of interest for MSE analysis. We did not impose any time restrictions during the task in order to capture the entire cognitive process and the associated brain activity. The EEG recording for the task lasted around 20 minutes, depending on the participants' time investment.

4.3.3.2 Numerical Simon task

To measure inhibition, we used a number-version of the Simon task (Fischer et al. 2008; Plessow et al. 2011). Participants were required to categorize numbers (1-9, except 5) as smaller or larger than five (i.e., identity as task-relevant stimulus dimension). Participants responded with the left key (Alt on a standard QWERTZ keyboard) and the right key (Alt-Gr) to numbers smaller and larger than five, respectively. Besides, all numbers were randomly presented either to the left or to the right of a fixation cross. The task-irrelevant stimulus location automatically activates the spatially corresponding response hand. In compatible conditions, this automatic response activation corresponds to the required response (e.g., number 9 presented on the right side). Incompatible conditions reflect a mismatch between automatic location-triggered response activation and the required response (e.g., number 1 presented on the right side). In this situation, top-down control is needed to suppress the incorrect automatic response activation (e.g., spatially corresponding right response) in order to correctly execute the required response (e.g., left response to number 1).

The task began with a practice block (16 trials). Each trial started with a fixation cross presented for 1000 ms and after which the target was added for 200 ms. The fixation cross lasted until a response was given or for max. 1600 ms. For every correct response, a blank screen was shown, for a missed response, and for an incorrect response, "falsch (false)" was shown as feedback. Afterward, the blank screen was presented for a random interval between 100 and 1000 ms. Participants performed three blocks[1] of trials including 80% compatible and 20% incompatible trials (96 and 24 trials per block). High frequency of compatible trials increases the reliance on automatic response activation, because the irrelevant stimulus location corresponds with the required response in most of the time. In rare incompatible trials, however, strong reactive inhibition is needed to control the incorrect automatic response activation triggered by the stimulus location. The difference between incompatible minus compatible trials denotes the Simon effect and represents a marker of stimulus-response conflict. Reaction times (RTs) and accuracies were recorded for each trial. The inhibition scores for modeling the behavioral performance on this task were obtained as RT difference scores between incompatible vs.

compatible conditions (i.e., mean RT in incompatible minus mean RT in compatible trials). Difference scores were calculated separately for the three blocks of trials, resulting in three indicators for modeling. These were rescaled so that the difference of the RT between the inhibition vs. non-inhibition trials presents reverse measure of inhibition (i.e., disinhibition). Thus, we expect individuals with larger difference can inhibit less and individuals with smaller difference would inhibit more. The difference scores of the RTs were used as indicators labeled as In1, In2, and In3. The EEG recording for the Simon task lasted approximately 12-15 minutes.

4.3.4 Data processing

4.3.4.1 Human-ratings of responses in the divergent thinking tasks

The behavioral DT data analyzed here were collected in a multivariate study and partially analyzed by Weiss et al. (2020). Thus, for further information on scoring and details on the DT tasks we refer to the previous study. The tasks were open-ended, hence, the responses required human coding. Therefore, three human coders were recruited who were semi-experts (psychology-students) regarding creativity and went through a training procedure prior to working on the ratings (following CAT; Amabile, 1982). The procedures were explained as follows:

1) Fluency (SA, IN, FF, RF): For the SA and IN tasks, the raters applied a typical fluency rating i.e., they counted the number of correct answers. The Intra-Class Correlations (ICCs; Shrout & Fleiss, 1979) across the fixed set of raters for all items of SA ranged between .96-1.00 and for IN was .93-.98. For the FF and RF tasks, the raters followed the test manual instructions on coding and the ICCs ranged between .89-.99 and .99-1.00, respectively. For each task, the ratings of the different raters were aggregated, resulting in a single mean score per item. Next, scores across items were aggregated as well to derive one task score each for SA, IN, FF, and RF which served as indicators for the latent variable modeling.
2) Originality (CO, NI): Every single response from the originality tasks was independently rated by each rater on a five-point scale based on proposed scoring guidelines from the literature (Silvia et al., 2008, 2009). A response was rated as

original if it was novel (uncommon), remote, and unexpected (clever) as compared to the rest of the sample (Silvia et al., 2008). The raters were instructed to rate the verbal creativity in relation to the answers given by other participants. Missed or inappropriate answers were rated as zero. Missing values in single tasks were taken as missing completely at random (nmax = 5 (6.5%), nmean = 2.67 (3.5%). The ICCs for originality were lower as compared to the fluency scores, but were acceptable. The ICCs for the task CO and for NI were between .56-.90. After estimating the ICCs, a compound score was calculated across all three raters for every item which served as indicators for the originality latent factor.

3) Verbal DT Task: For the verbal DT task applied during the EEG recording, also three trained native German speakers rated all responses, for detailed information on the ratings please see Kaur et al. (2020). The results of the ratings showed that the individuals indeed produced more creative verbs in original as compared to the typical association condition.

4.3.4.2 Pre-processing of the EEG datasets

The EEG data were preprocessed in MATLAB and were offline filtered using IIR (zero phase shift), and Butterworth filters between 0.1-50 Hz (order = 2; time constant = 1.59 s) and recalculated to average reference using Brain Vison Analyzer (Brain Products, Germany). Further pre-processing steps were executed in EEGLAB (Delorme & Makeig, 2004). The artifacts due to blinks and eye movements were handled by applying independent component analysis (ICA; function: runica). Further, SASICA (EEGLAB plugin; Chaumon et al., 2015) was used as a guide to select artefactual components.

4.3.4.3 Multiscale Entropy Analyses

MSE is an information-theoretic metric that characterizes the variability of temporal signals, i.e., EEG across multiple temporal scales from a perspective on signal complexity (Costa et al. 2002, 2005). The basic rationale of MSE is that multi-scale analysis provides more detailed insight into the underlying biological processes as compared with single-scale methods (e.g.,

approximate entropy). The multi-scale approach approximates the system dynamics on different time scales which are then analyzed with the sample entropy (SampEn) algorithm. There are two critical parameters in the algorithm: m defines the length of the signal patterns which are compared with each other and *r* is the similarity bounds within which the signal patterns are matched. The MSE algorithm consists of two steps:

1) coarse-graining of the signal time series at multiple time scales which means averaging the data inside a window of length τ in order to reduce the high-frequency components. Coarse-graining is implemented by replacing the progressively increasing number of data points in non-overlapping windows by their average values to form a new time series (for illustration see Costa et al. 2002; Kaur et al. 2019, 2020). The coarse-grained time series at time scale 1 is identical to the original signal; at scale *i*, the time series is divided into non-overlapping windows to be concatenated, each of which contains i points corresponding to the time scale.
2) SampEn is then calculated for each of those coarse-grained time series. SampEn identifies the repetition of sequence pattern in the time series and calculates entropy as follows: The number of patterns with *i* data points satisfying the similarity bounds *r* need to be identified. These are counted and denoted as *N*(*i*). Then, the number of similar sequences with *i*+1 data points are counted and denoted as N(*i*+1). Finally, SampEn has calculated as the negative logarithm of the conditional probability that two similar sequences of *i* data points will be similar for the next *i*+1 points:

$$SampEn(i) = -ln\frac{N(i+1)}{N(i)} \tag{4.1}$$

Therefore, two sequences are considered to be similar if the differences between each of the paired data points of the two sequences (i.e., *N*(*i*) and *N*(*i*+1)) fall within the range of *r*. Tradition-ally, the *m* is fixed to the value 2 and *r* as 15% of the *SD* of the original time series being analyzed. Therefore, for the present work, we applied these parameter settings.

4.3.4.4 Interpreting MSE Time Scales

As previously mentioned, theoretically small/fine time scales of the MSE are taken to represent activities and fluctuations in local neural networks, whereas large/coarse time scales, are interpreted as representing activities across more widely distributed neural networks (Grundy et al., 2017; Vakorin et al., 2011). The interpretation can be simplified in the real-time domain. For example, in the present study, we computed MSE in the two experiments (i.e., verbal DT and Simon task) for the time scales 1-20 and 1-10, respectively. Based on the sampling rate (250Hz) used in the present work, the real-time sampling interval at scale 1 is 4 ms. Therefore, MSE at scale 1 reflects dynamical activities of the neural system at a resolution of 4 ms, which captures fast and slow dynamics. In a similar vein, scale 5 reflects dynamical activities of the brain slower than a resolution of 20 ms and scale 10 indicates activity at 40 ms resolution. At the largest scale 20, the activity is at 80 ms resolution and reflects slow brain dynamics. Thus, at smaller time scales, MSE mainly reflects fast and, hence, local neural activities, whereas at larger scales MSE mainly captures slow dynamics across broader spatial domains. However, a new study by Kosciessa et al. (2020) argues against such a traditional interpretation of MSE time scales based upon direct scale-to-frequency mapping. The study demonstrated that entropy at fine time scales is highly sensitive to broadband spectral power which is dominated by low-frequency contribution. This new line of work challenges the implementation of similarity bounds *r* (by which the signal *SD* is multiplied). Traditionally, *r* is not equally liberal across all time scales because it is used as *r*SD* of the original time series i.e., *r*SD* will be used for all time scales. As Kosciessa et al. (2020) demonstrated, this approach leads to biased entropy estimation. The signal during MSE analysis is successively coarse-grained at different time scales, except scale 1, which is similar to low-pass filtering. But the *r* is calculated only relative to the SD of the original, unfiltered signal (at scale 1). However, successive coarse-graining reduces the SD of the signal, and as a result signal variance is normalized which introduces biased entropy estimation if it was calculated with a constant *r*. Therefore, the authors suggest computing the similarity bounds for each scale factor. Following these suggestions, we additionally performed global similarity bounds or scale-wise *r* MSE analysis. The results are provided in supplementary material S1 (https://osf.io/sg9e2/). They reveal that the traditional MSE and scale-wise *r* MSE did not considerably differ in this particular

application. Therefore, multivariate analyses reported in the main part of the paper were based upon traditional MSE analyses using invariant-*r* (or global similarity bound), because as such the results can be directly compared with our previous study (Kaur et al., 2020).

4.3.4.5 MSE computation using the EEG signals acquired during the verbal divergent thinking and the numerical Simon task

The lengths of trials in the verbal DT task (typical and original associations) varied from trial-to-trial and person-to-person (for more details see Kaur et al., 2020). Because we aimed to capture the complete idea generation process the signal across all trials of varied length was concatenated separately for each condition. The MSE scores calculated during the production of typical associations are referred as MSE in fluent neural states and MSE calculated during the production of original associations are referred to as MSE in creative neural states. The same procedure was applied for the Simon task. The length of the trials varied but due to frequent compatible and fewer incompatible trials, it was critical to standardized the length across the two conditions. Therefore, we concatenated the trials of the EEG time series for each condition and then selected 2500 data points (10 seconds) from each condition. The MSE scores were calculated for the concatenated incompatible trials which were labeled as MSE in inhibition and for the concatenated compatible trials were labeled as the MSE in non-inhibition. Additionally, we subtracted the MSE scores of non-inhibition from the MSE scores of inhibition to obtain a difference score inhibition measure for our fourth research question (see above). These neural indicators of inhibition were calculated for each participant, at each electrode across multiple time scales (ranging from scale 1-10). The trial length in the Simon task was short. This is the reason for calculating MSE in this task only up to time scale 10. As systematically illustrated by Li et al. (2020), the reliability of MSE decreases with decreasing length of the time series.

4.3.4.6 Integrated MSE scores using Area Under the Curve (AUC) measures

MSE analyses provide entropy values for each electrode and time scale. Thus, for statistical analyses, it is advisable to integrate these values, given their interpretation is equivalent. Hence, we integrated MSE values across several scales into a single score by using the Area Under the Curve (AUC). This integration procedure has been previously proposed in the literature because

low and high scales are interpreted differently, but interpretations do not differ for neighboring scales (see Kaur et al., 2019; Li et al., 2020; Takahashi et al., 2009). For a data-driven division of time scales in high and low in case of the verbal DT task, we visually inspected the line-plots of grand-mean MSE during the production of typical vs. original associations (see also Kaur et al. 2020). The line plots suggested that the MSE difference between the two experimental conditions increases across small scales (1-5), shows a rather stable condition difference at medium scales (6-15), but no difference at large scales (16-20). Therefore, we divided the time scale-specific MSE values into three categories: small scale MSE, ranging from scales 1-5; medium scale MSE, including scales 6-15, and large scale MSE from scale 16-20. We integrated the person- and condition-specific MSE values by summing them up across those scales resulting in three AUC scores: small-, medium- and large-AUC scores for every individual and condition. For the Simon task, we categorized the scales into small (1-5) and medium time scales (6-10; see grand-mean MSE line-plots of the Simon task in Figure S2, supplementary material S2; https://osf.io/sg9e2/). Additionally, to investigate the difference between each task condition and their associations with behavioral outcomes of creativity and intelligence, we computed the difference scores of MSE in creative and inhibitory neural states. Difference scores across experimental conditions are conceptually better indicators for inhibition and creativity because they reflect the specificity of a neural signal as compared with a baseline condition. However, difference scores might have poor psychometric qualities (Rogosa & Willett, 1983), thus we explore both difference scores and simply the signal in the respective task condition in their relation with behavioral creativity and intelligence. The largest difference between the task conditions occurs in medium time scales in original and typical associations and small time scales for inhibition and non-inhibition conditions. Thus, for the AUC scores, we calculated the difference between small-AUC in inhibition vs. non-inhibition and medium-AUC in original vs. typical associations. The difference was calculated by subtracting small-AUC in non-inhibition from inhibition condition and medium-AUC in typical from the original association. The average medium-AUC difference between the original vs. typical association was positive and between small-AUC values of inhibition vs. non-inhibition was negative (see below).

4.3.4.7 Statistical Analyses

We applied Structural Equation Modeling (SEM) by using the R Software for Statistical Computing (Team R. C. 2018). For SEM estimation, we used the lavaan (LAtent VAriable ANalysis) package by Rosseel (2012). SEM is a generalized linear modeling framework proposed as a combination of confirmatory factor analysis and path modeling. For an introduction to SEM, we referred to Kline (2015). The behavioral measurements of gf, gc, fluency, originality, and inhibition served as indicators of the latent variables. SEM allowed us to test associations at the level of latent variables which are adjusted for measurement error. Furthermore, SEM allows quantifying individual differences (as factor scores) and investigating brain-behavior associations on their basis. Note that the limited sample size does not allow to test latent brain-behavior association models. Model fit was evaluated by the following test statistics and fit indices: The chi-square fit statistic ($\chi 2$), the comparative fit index (CFI, that should exceed .95 for a good fit), standardized root mean square residual (SRMR, to be lower than .08), and root mean square error of approximation (RMSEA, to be lower than .08). Missing data were handled by the full information maximum likelihood method as implemented in lavaan.

4.4 Results

4.4.1 Individual Differences in Creativity, Intelligence, and Inhibition

We estimated two SEMs to examine the relationship between creativity, intelligence, and inhibition. In Model 1, behavioral scores of gf, gc, fluency, and originality were used to estimate four correlated factors as illustrated in Figure 4.1. In Model 2, the correlated factors of gf, gc, fluency, and originality were then regressed onto a fifth inhibition factor. Figure 4.1 illustrates the model structure with factor loadings and latent correlations, as well as path coefficients estimated in Model 1 (blue) and 2 (green).

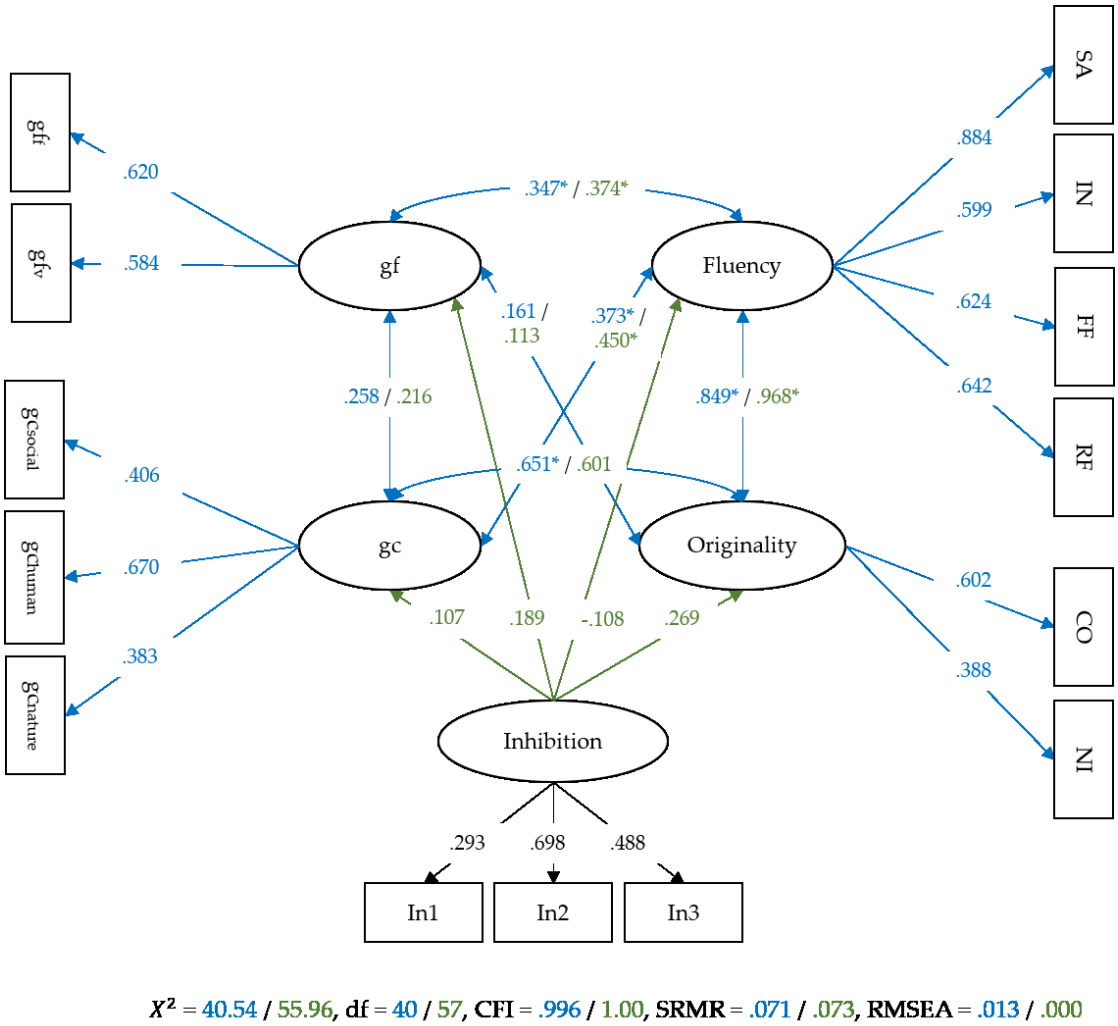

Figure 4.1. Simplified schematic presentations of the SEMs estimated to investigate the relationship between creativity, intelligence, and inhibition. The numbers are color coded to indicate parameter estimates from the two different models: Blue coded parameter estimates and model fit indices belong to Model 1 and green coded ones to Model 2. Loadings are only provided for Model 1 as they did not considerably differ in Model 2. The latent factor fluency is measured by four indicators, similar attributes (SA), retrieval fluency (RF), figural fluency (FF), and inventing names (IN). The latent factor originality is measured by combining objects (CO), and nicknames (NI). Fluid intelligence (gf) has two indicators, figural fluid intelligence (gff), and verbal fluid intelligence (gfv). Crystallized intelligence (gc) tasks assessed knowledge in three domains natural sciences (gcnature, humanities (gchuman), and social studies (gcsocial). Inhibition was measured by three reaction time difference scores between the inhibition and non–inhibition conditions of the Simon task, labelled as In1, In2, and In3. Note that loadings on the gf and Originality factors were restricted to essential tau-equivalence for the respective factor. This is for the measurement model to be identified with two indicators only. Thus, non-standardized factor loadings of gff and gfv were restricted to equality, and CO and NI were fixed to be equal as well. As reflected in model fit, these restrictions were reasonable. Residuals are not displayed but were all estimated. Significant associations are indicated by the asterisk sign (*, $p < .05$).

Model 1 had a very good fit: $\chi 2$ (40) = 40.54, p = .44, CFI = .996, SRMR = .071, RMSEA = .013. The latent factors of gf and fluency showed a moderate positive relationship (r = .347, p =.033). Stronger relationships were observed between fluency and originality (r = .849, p < .001) and originality and gc (r = .651, p = .030). Weak and non-significant associations were observed between gf and

originality (r = .161, p =.510) and gc and gf in the present quite small sample (r = .258, p = .358). Finally, gc and fluency showed a moderate, statistically significant association (r = .373, p =.041).

In Model 2 gf, gc, fluency, and originality were regressed onto inhibition. The fit was as follows: $\chi 2$ (57) = 55.96, p = .514, CFI = 1.00, SRMR = .073, RMSEA = .00. The inhibition factor showed weak and non-significant associations with gf (β = .189, p =.418), gc (β = .107, p =.732), originality (β = .269, p = .303), and negative on fluency (β = -.108, p =.586). Given the small sample size of this study not even the inhibition-originality association reached statistical significance. However, when controlling for inhibition some association between intelligence and creativity factors slightly changed (see Figure 4.1). This is indeed no strong evidence, given that the associations between inhibition and the four factors were not substantial. Note that the same partial correlations were also tested at the level of observed variables, after aggregating the indicators of gf, gc, fluency, and originality, as well as inhibition. However, none of the partial correlations between intelligence and creativity facets substantially differed from the correlations not being controlled for inhibition. In conclusion, at the behavioral level, we do not find support for the explanatory role of inhibition in the intelligence-creativity association. Potential reasons will be discussed. As next, we aim to explore the relationship of inhibition, intelligence, and creativity at the neural level.

4.4.2 MSE as a Neural Marker of Inhibition

To explore inhibition as a correlate of intelligence and creativity at the neural level, we first need to test whether MSE is a sensitive measure to differentiate inhibition and non-inhibition states. Thus, to address this question across multiple time scales of MSE, we inspected the topographical pattern of the MSE difference between the two conditions across the scalp. For this purpose, we computed the difference for single scale MSE measures as well as the AUC scores between the two experimental conditions by subtracting non-inhibition MSE from the inhibition MSE. Figure 4.2, Panel (a) provides the topographic plots of the grand-mean MSE difference between the two conditions across 10-time scales.

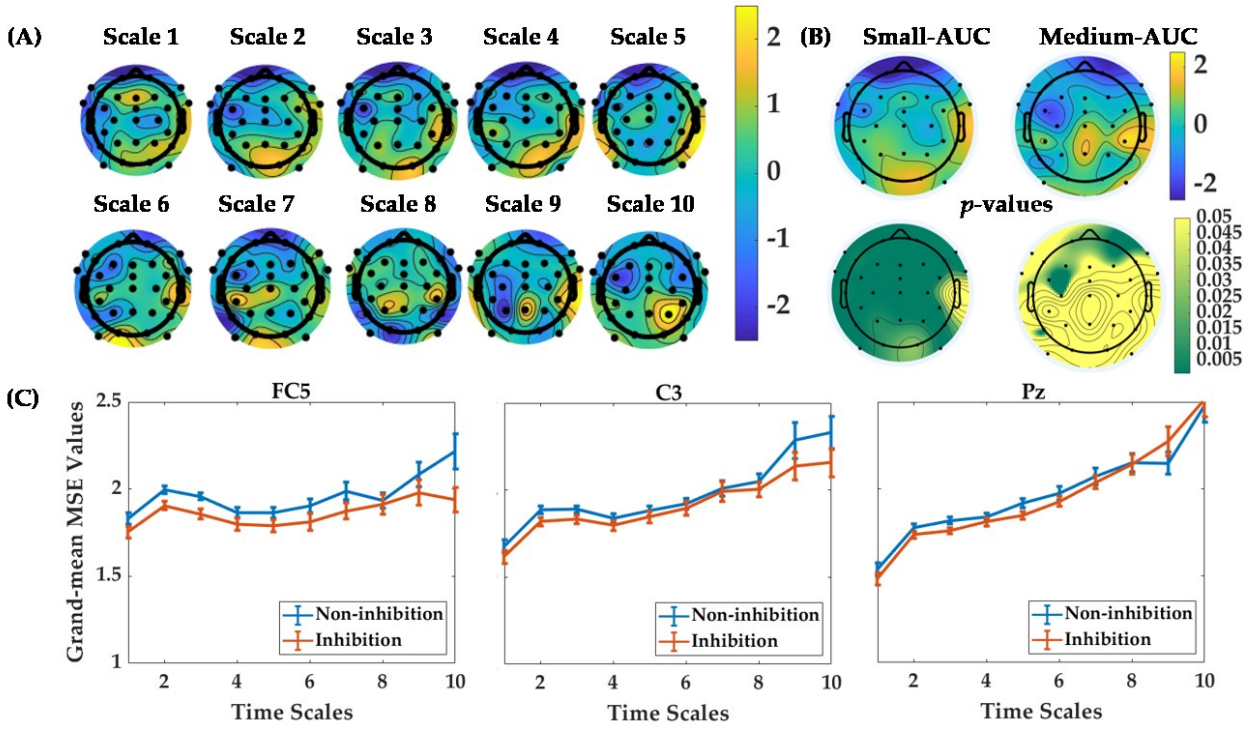

Figure 4.2. Illustration of the MSE difference between inhibition and non-inhibition conditions. Panel (a) shows the topographic plots of MSE difference scores between the two conditions across 10 time scales. The color bar indicates standardized MSE values on a *z*-scale. The yellow color indicates positive and the dark blue negative differences. The top row of Panel (b) displays the topographic plots of the grand-mean MSE difference between the two conditions for the small- and medium-AUC values. The bottom row shows the corresponding *p*-values of the difference scores. Panel (c) illustrates the grand-mean MSE line-plots for the two conditions across 10 time scales at three representative electrodes namely FC5, C3, and Pz. These electrodes were selected based on the strongest difference exhibited in the single scale MSE and the AUC difference topo plots and their statistical significance after correcting for multiple testing (dark green in the *p*-value topoplots). Error bars represent standard errors of the mean.

Generally, a positive difference (yellow coded in Figure 4.2, Panel (a)) occurred at small time scales (1-4) in most central and parietal electrodes. At medium time scales (6-10), a positive difference is visible on the CP5, P3, Pz, CP6, and P4 electrodes. The top row of Panel (b) displays the topographic plots of the difference between the two conditions for integrated small- and medium-AUC values. The bottom row represents the corresponding p-values of the difference scores in form of topographic plots. As indicated by these four plots, the most substantial differences between the two conditions across the scalp occur in the small-AUC as compared to medium-AUC for which the *p*-values do not survive correction for multiple testing. The small-AUC difference plot shows statistically significant differences across the entire scalp (as depicted in the dark green color of the *p*-value plots). The medium-scale-AUC difference plot shows only a few statistically significant effects at frontal electrode sites with a considerably low *p*-value (<.005, corrected for multiple testing). Panel (c) illustrates the line-plots of the grand-mean MSE

in the two conditions for electrodes FC5, C3, and Pz. These electrodes were selected for illustration because they show the most substantial differences between the conditions in the small-AUC range. The line-plots illustrate that MSE in inhibition condition is reduced as compared with the non-inhibition condition across small time scales at frontal and central electrode sites. This is in line with the notion that the dynamic neural system becomes locally more focused with challenging information input (conflict as compared with non-conflict trials) to deal with (see Kaur et al. (2019) for a systematic demonstration across different brain states and the discussion below).

4.4.3 MSE in Inhibition as a Correlate of MSE in Verbal Creativity

In 4.4.2 we demonstrated that MSE is a sensitive neural marker of inhibition at low time scales and fronto-central electrode sites. Next, we investigated the relationship between inhibition and creativity at the level of neural signal complexity. For this purpose, we used the AUC scores of MSE measured during verbal creativity vs. inhibition. Our previous study (Kaur et al., 2020) demonstrated the strongest difference between the typical and original association conditions at the medium time scales of MSE (see also supplementary material S1; https://osf.io/sg9e2/). Further, as shown above, small time scales showed the most substantial differences between the inhibition and non-inhibition condition across the entire scalp. Thus, we correlated AUC scores from the medium time scales of MSE in creativity and the small time scales of MSE in inhibition task conditions. Figure 4.3 illustrates these correlations in the form of topographic and scatter plots.

Panel (a) shows Pearson correlations between the respective AUC-MSE scores measured during original association vs. the inhibition states. The plot on the right side illustrates corresponding *p*-values. Similarly, the plot at the left side of the Panel (b) provides scalp topographies of Pearson correlations between MSE in typical association vs. inhibition condition, at the right side with the corresponding *p*-value plot.

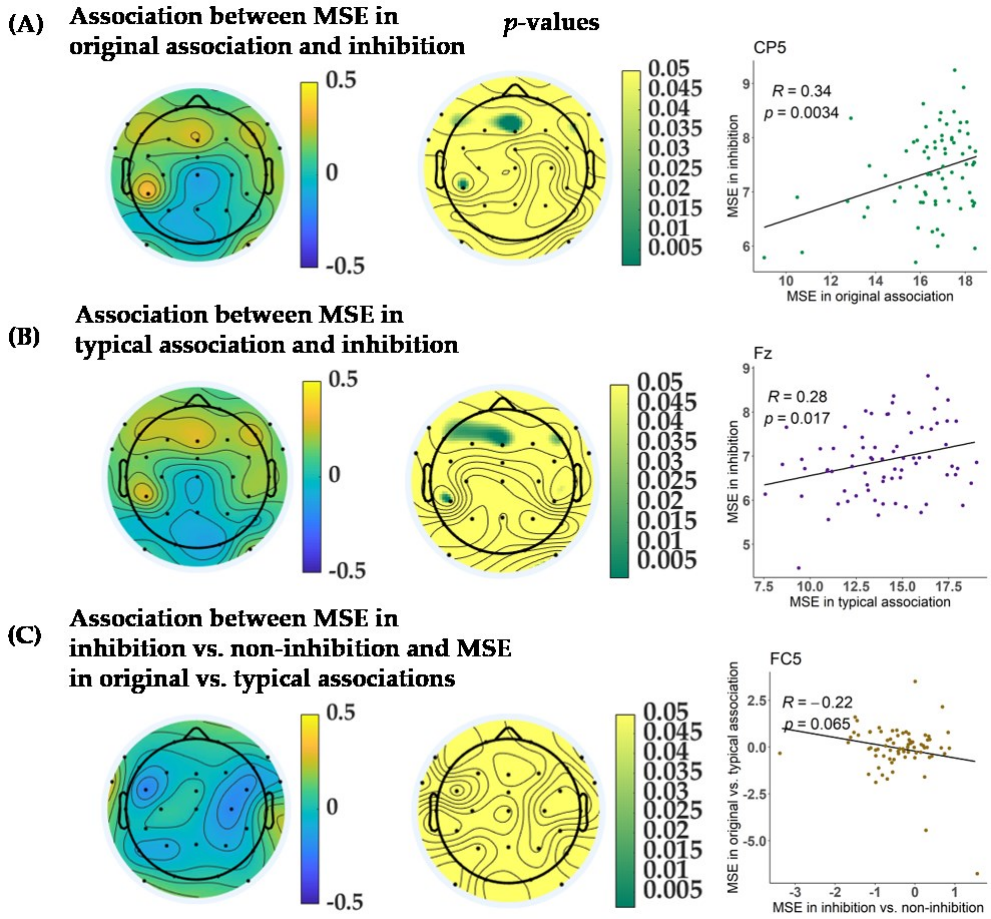

Figure 4.3. Associations between the grand-mean MSE in creativity and inhibition. The left topographical plot in Panel (a) shows Pearson correlations between medium-AUC values of MSE in original association and small-AUC values of MSE in inhibition. Similarly, the left plot in Panel (b) shows Pearson correlations between medium-AUC in typical association, and small-AUC in inhibition. The right topographical plots in both panels provide the corresponding *p*-values of the correlations displayed on the left side. The yellow color on the left topographical plots indicate positive correlations and the green color in the right side plots indicate statistical significance after correction for multiple testing. The scatter plots on the right side of both panels illustrate the strongest and substantial association at CP5 and Fz electrodes. Panel (c) illustrates Pearson correlations between the difference scores of the small-AUC in inhibition and medium-AUC in verbal creativity. The strongest negative association was at FC5.

As depicted in the left plots of both panels, moderate and statistically significant correlations are prominent in the frontal and left centro-parietal sides of the scalp after correction for multiple testing (dark green *p*-values < .005). Thus, positive and statistically substantial associations were observed at the electrodes F7, F8, Fz, CP5, and PO10. Additionally, the scatter plots on the right-side of each panel depict the strongest associations between the neural measures of creativity and inhibition which were observed at CP5 and Fz electrodes. The scatter plots for all other electrodes at which the correlations were statistically significant after correction for multiple testing are provided in the supplementary material S3 (https://osf.io/sg9e2/). The above results are in line

with our speculations that MSE in inhibition is positively associated with MSE in creative brain states at frontal electrodes. The results further illustrate a somewhat stronger and more robust association of inhibition and originality MSE (r = .34, p = .003) than inhibition and fluency MSE (r = .28, p = .017). Further, we examined whether MSE in inhibition would explain the relationship between MSE in creative vs. typical association. We thus computed partial correlations between the MSE in creative vs. typical association states controlling for MSE in inhibition condition. The observed correlation between the two conditions was high (r = .95, p < .001). After controlling for MSE in inhibition, their association did not drop substantially (r = .94, p < .001). For more details, see supplementary material S4 (https://osf.io/sg9e2/). In conclusion, at the level of MSE associations, we do not find support for the explanatory role of inhibition in the fluency-originality association.

Finally, we aimed to explore the association between the MSE difference scores measured during verbal creativity (original vs. fluent) and inhibition (inhibition vs. non-inhibition). For this purpose, we visually explored the topographical pattern of the correlations between the difference in AUC scores in the two experimental conditions of each task. The left side plot of Panel (c) illustrates these correlations across the scalp. The right side plot provides the corresponding p-values. The scatter plot on the right side shows the association between the difference scores at the FC5 electrode. The topographical and scatter plots with the corresponding p-values indicate that the association between the neural difference scores of inhibition and originality was mostly negative at frontal and temporal electrode sites. This indicates that the more the neural system reduces its complex activity to focus and deal with disrupting and conflicting information input (negative difference between inhibition and non-inhibition conditions, see 4.4.2.), the more complexity it exhibits when creative associations are expected. The magnitude of the observed associations is however small, -.20 and they do not survive correction for multiple testing. Nevertheless, these associations are thrilling and should be followed up in future studies on larger samples (see Discussion below).

4.4.4 On the relationship between grand-mean MSE in creative and inhibitory neural states with individual differences in gf, gc, fluency, and originality

To explore further, we examined how grand-mean MSE in creative and inhibitory neural states relate to behavioral outcomes of gf, gc, fluency, and originality. We first estimated individual factor scores extracted based on Model 1 as illustrated in Figure 4.1. Factor scores were estimated using the function lavPredict() in lavaan which for quantitative data relies on Bartlett (Bartlett, 1937) method. Individual factor scores for each latent variable were used to investigate brain-behavior associations. Importantly, to validate the factor scores, we tested correlations between the factor scores and their corresponding latent variables (i.e., gf, gc, fluency, and originality) as suggested in the literature. The results yielded high correlations (see supplementary material S5). Thus, we conclude that factor scores can be taken as ability estimates. Next, we computed Pearson correlations between obtained factor scores and medium-AUC in original associations and small-AUC in inhibition. Figure 4.4, Panel (a) and (b) provide topographical plots of these correlations for gf, gc, fluency, and originality, as well as their corresponding *p*-values. The correlations between typical association with behavioral outcomes are provided in supplementary material S6. As depicted in the left and right side plots of Panel (a), the only moderate correlation between MSE in original association and gf was observed at the P8 electrode. However, the association does not survive correction for multiple testing. In the case of gc, none of the associations were substantial. Fluency and MSE in originality showed positive and significant association at FT10, P3, and Pz electrodes (see supplementary material S7; https://osf.io/sg9e2/) with the strongest association being observed at electrode FT10. The strongest positive and substantial association between originality and MSE in originality was observed at the P3 and Pz electrodes. Panel (b) shows that a small correlation between gf and MSE in inhibition was observed at T7 which however did not survive correction for multiple testing. The correlations with gc were mainly negative and strongest at the FT9 electrode. The associations between MSE in inhibition and fluency were statistically significant at Cz, FC5, O1, T8 and the strongest positive association was at the O2 electrode. Originality showed substantial associations with MSE in inhibition states at

T8 and O2 electrodes. The scatter plots of all mentioned substantial associations are provided in the supplementary material S7 (https://osf.io/sg9e2/).

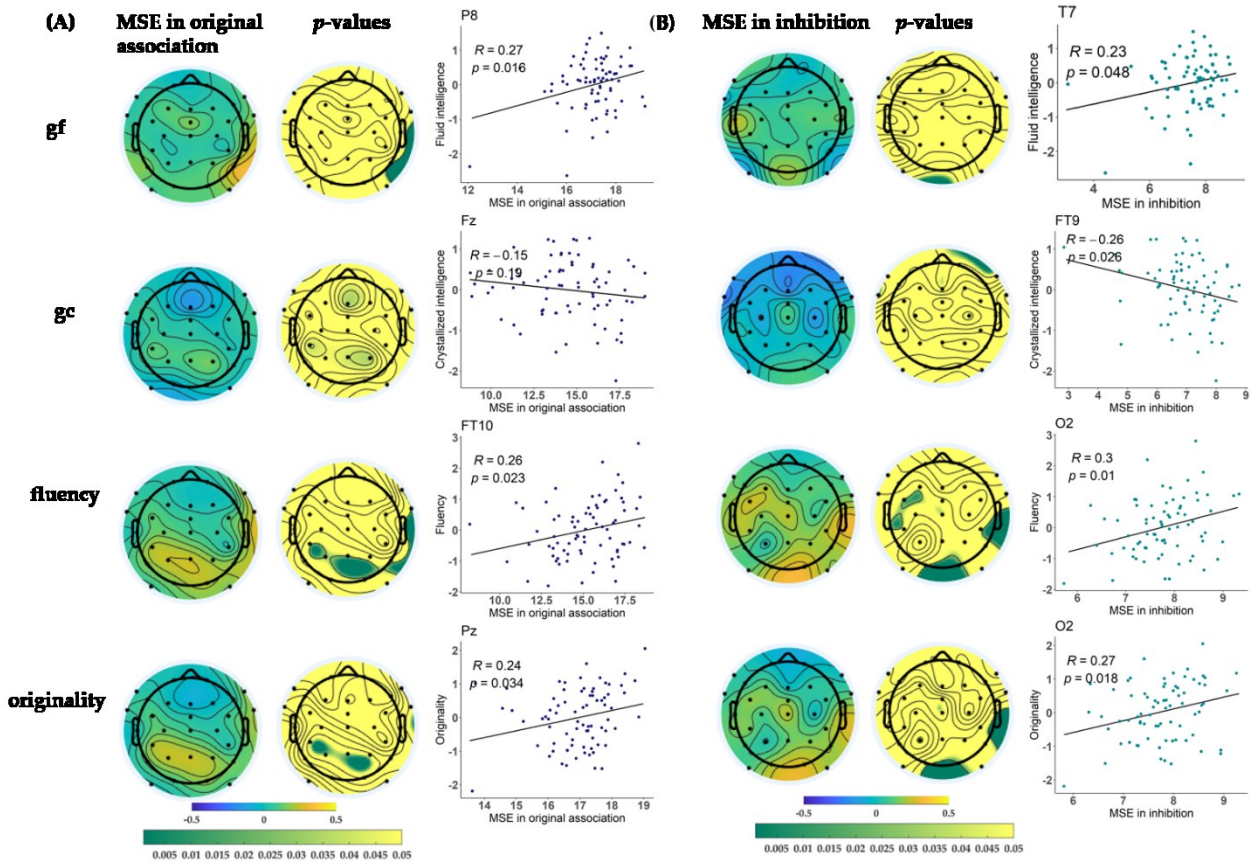

Figure 4.4. Correlations between grand-mean MSE in original associations and inhibition with gf, gc, fluency, and originality. The left topographical plots in Panel (a) show Pearson correlations between medium-AUC values of MSE in original association and factor scores of gf, gc, fluency, and originality. The topographical plots on the right side of each panel show corresponding *p*-values, dark green color indicating statistical significance after multiple test correction ($p < .005$). The scatter plots on the right side illustrate the strongest associations among other electrodes, which were at P8 and Fz and at FT10 and Pz electrodes, respectively. Similarly, Panel (b) shows Pearson correlations between small-AUC values of MSE in inhibition and factor scores of gf, gc, fluency, and originality. The corresponding *p*-values and scatter plots illustrate strongest and substantial associations at T7, FT9, and O2 electrodes.

4.4.5 On the relationship between MSE difference scores with gf, gc, fluency, and originality

As the last step of our intended explorations to answer research question 5, we tested associations between the difference scores of MSE in creative and inhibitory neural states with behavioral outcomes of gf, gc, fluency, and originality. As the last step of our intended explorations to answer research question 5, we tested associations between the difference scores of MSE in creative and

inhibitory neural states with behavioral outcomes of gf, gc, fluency, and originality. Figure 4.5, Panel (a) and (b) provide topographical plots of correlations between factor scores of gf, gc, fluency, and originality and the MSE difference between original vs. typical associations and MSE difference in inhibition vs. non-inhibition respectively, as well as their corresponding *p*-values.

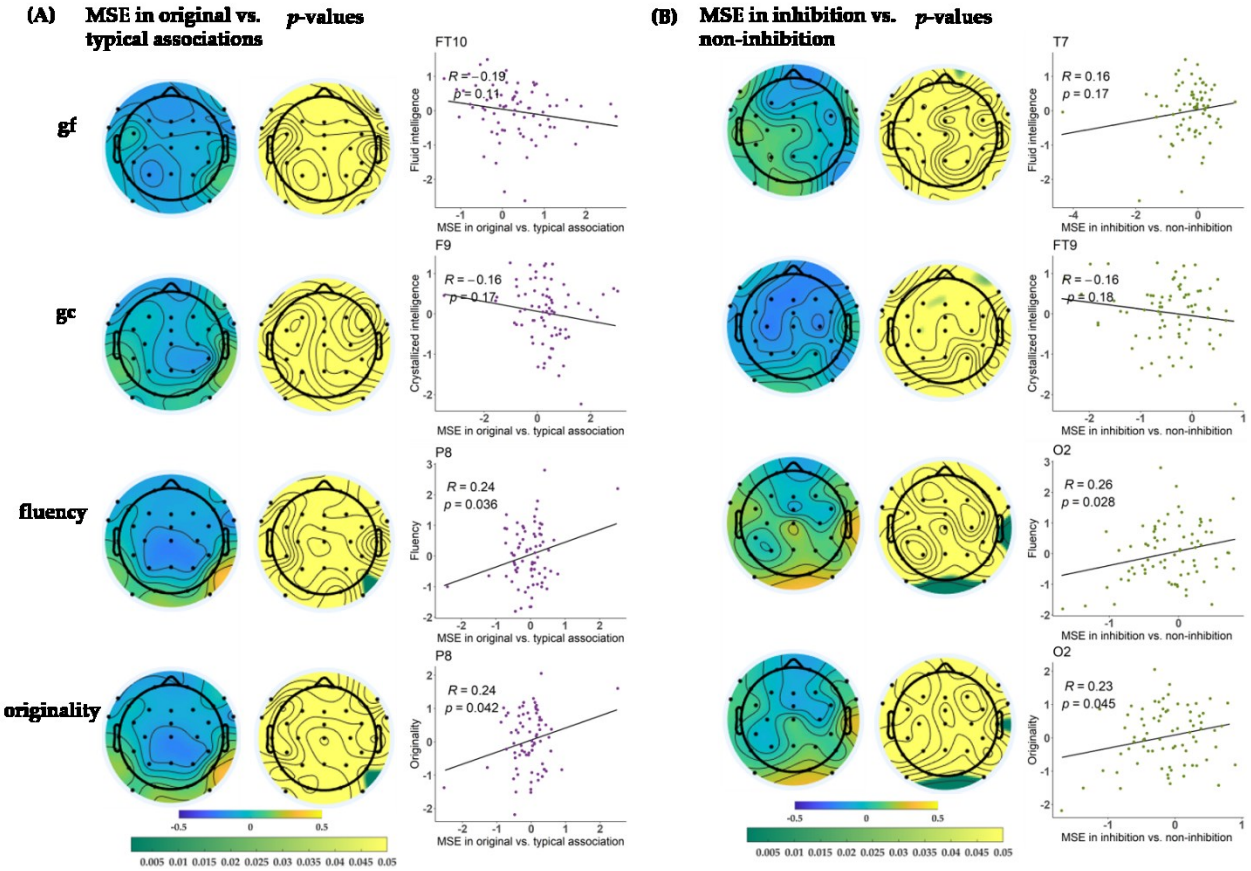

Figure 4.5. Correlations between difference of grand-mean MSE in original vs. typical associations and difference of MSE in inhibition vs. non-inhibition conditions with gf, gc, fluency, and originality. The left topographical plot in Panel (a) show Pearson correlations between difference of medium-AUC values of MSE in original vs. typical association and factor scores of gf, gc, fluency, and originality. The topographical plots on the right side of each panel show corresponding *p*-values, dark green color indicating statistical significance after correction for multiple testing ($p < .005$). The scatter plots on the right side illustrate the strongest association at P3 and P4 electrodes. Similarly, Panel (b) shows Pearson correlations between difference of small-AUC values of MSE in inhibition vs. non-inhibition and factor scores of gf, gc, fluency, and originality. The corresponding *p*-values and scatter plots illustrate strongest associations at T7, FT9 and substantial, but unexpectedly positive associations at O2 electrodes with fluency and originality.

As depicted in Panel (a), the correlation between the difference scores of medium-AUC in the creativity task and gf were small and did not survive correction for multiple testing. The scatter plot on the right side shows a weak association at the FT10 electrode. In the case of gc, there were no substantial associations across the entire scalp. With fluency and originality, the strongest

association was at the P8 electrode. Other associations were mainly negative but did not survive correction for multiple testing.

Panel (b) shows that none of the correlations between the difference scores of small-AUC in inhibition vs. non-inhibition and gf, gc were substantial. Counterintuitively, association with fluency and originality was strongest at occipital electrodes, indicating individuals with a positive difference score between inhibition and non-inhibition MSE to be more fluent and more original. This is not in line with the assumption that individuals with a stronger negative difference are adapting their neural system better to conflicting incoming information. Further, scatter plots are provided in the supplementary material S8 (https://osf.io/sg9e2/). The topographical plots show for all abilities a series of negative associations at fronto-central electrodes which however did not survive correction for multiple testing.

4.5 Discussion

The present study aimed to explore the relationship between creativity, intelligence, and inhibition, specifically focusing on EEG signal complexity. Because no previous comparable studies exist, a hypotheses-generating approach seemed more appropriate. However, we had some á priori expectations with respect to the association patterns between these constructs at the behavioral and neural level derived from adjacent neuroscientific literature on creativity measured by verbal DT task, knowledge, and reasoning, as well as temporal complexity of neural signals and their changes depending on different tasks conditions (e.g., Kaur et al., 2019). A large amount of association tests based on the data at hand, given correction for multiple testing only partially supported those predictions. Nevertheless, the described scalp patterns and magnitude of associations arguably provide valuable information for designing future confirmatory studies on neural complexity approaches to DT and intelligence, using MSE, but also other signal complexity measures, such as for example non-oscillatory (1/f) signal components (see Ouyang et al., 2020). We will first summarize the present findings and discuss thereafter how these findings advance our knowledge about the neural dynamics underlying creativity as well as the understanding of the link between facets of creativity and intelligence.

4.5.1 Summary of Findings

At the behavioral level, we replicated (for a review see Silvia, 2015) the positive creativity-intelligence relationship concerning their facets gf and gc vs. fluency and originality. However, we could not replicate and extend previous findings (Benedek et al., 2014) according to which inhibition partly explains the relationship between creativity and intelligence. Differently from previous studies, we have investigated these relations based on a multivariate study that includes a broad range and number of indicators for intelligence and DT. However, inhibition was only measured with one task. A further disadvantage of the present study is that our sample size was low for latent variable modeling. Most importantly, as compared to the measurement approach by multiple tasks of DT and intelligence, inhibition was only measured based on one single task in the present exploratory study design.

At the neural level, we discovered that brain signal complexity can be considered a neural marker of inhibition. This was indicated by a quantitative difference between MSE in inhibition and non-inhibition neural states, especially at small time scales. Specifically, we found that the dynamical neural system responds with decreased complexity in local brain networks to focus attention and deal with conflicting information when such needs to be handled in a cognitive task.

Further, we found that MSE in inhibition is specifically correlated with MSE in original verbal association production, but also positively associated with MSE in typical verbal association production. These findings revealed that the grand-mean MSE in inhibition was moderately associated with the grand-mean MSE in creative neural states. Importantly, in line with our assumptions, we found small but thrilling associations between the MSE difference in inhibition vs. non-inhibition and verbal creativity (original vs. fluent) which were mostly negative across the scalp. Even if these small associations did not survive the correction for multiple testing, they are thrilling because they indicate stronger neural inhibition to foster neural complexity needed for the generation of more creative associations (see also Kaur et al., 2020).

Finally, we explored associations between MSE in inhibition, fluent, and creative neural states with individual differences in gf and gc, as well as fluency and originality. Findings revealed some

substantial associations between MSE in original neural states with fluid intelligence, fluency, and originality. However, surprisingly these occurred at parietal electrode sites and not at fronto-temporal ones for which the neural complexity difference between creative and fluent association states was strongest according to Kaur et al. (2020). MSE in inhibition was significantly associated with individual differences in gf and gc, as well as fluency and originality. More importantly, we also explored ability and MSE difference score associations for original vs. fluent neural states and inhibition vs. non-inhibition states. The MSE difference in original vs. fluent neural states showed a few substantial associations with individual differences in behavioral fluency and originality at parietal electrodes. The MSE difference in inhibition vs. non-inhibition neural states was substantially associated with fluency and originality in occipital regions. Whereas the former indicated neural complexity increase when creative responses are expected to be beneficial for behavioral fluency and originality, the latter indicated less focused local neural dynamical activity in cognitive conflict (negative difference between inhibition and non-inhibition conditions, see 4.4.2) to be detrimental for fluency and originality. This is contradictory to the notion suggested in the literature (Benedek et al., 2012; Camarda et al., 2018; Zabelina & Ganis, 2018) according to which stronger inhibition facilitates creativity.

Taken together, our study extends the understanding of the creativity-intelligence-inhibition relationship at the level of neural signal complexity, demonstrating common and differential involvement of inhibition in fluency and originality, as well as the relationship between intelligence and creativity. We will now elaborate on the above and point to potential future study directions.

4.5.2 Individual differences in creativity, intelligence, and inhibition

Our study aimed at extending hitherto available findings on the explanatory role of inhibition to understand the nature of the associations between creativity (facet fluency and originality) and intelligence (gf and gc). The four correlated latent factors of fluency, originality, gf and gc showed relationships of different magnitude which were mostly in line with the previous literature. The fluency and originality factors were strongly associated. Several studies, have demonstrated that fluency and originality, despite being conceptually different aspects of DT, are highly associated

even if measured by independent tests (e.g., Silvia, 2008; Weiss et al., 2020). The present study is in line with these findings and with further literature indicating strong positive relationships between fluency and originality (Dumas & Dunbar, 2014; Runco, 2010; Silvia, 2008).

The revealed moderate correlation between fluency and gf was slightly lower than what has been typically observed in the literature (Beaty & Silvia, 2013; Benedek et al., 2014). However, the moderate association might be due to larger measurement bias in a rather small sample size as compared with previous behavioral studies.

Further, gc was moderately associated with fluency and showed strong associations with originality indicating that the generation of creative ideas requires adequate recombination of unrelated semantic concepts (Koestler, 1964; Mednick, 1962). gc is the intellectual ability that individuals accumulate through vocabulary and factual knowledge. Therefore, in verbal creativity tasks, especially when individuals are required to produce unique and context-appropriate answers, they need knowledge as a source for association generation. Individuals need to integrate various mental strategies which they would retrieve from relevant domain knowledge within a malleable problem space (Runco & Acar, 2012). Therefore, gc would assist by allowing individuals to retrieve knowledge from specific domains to generate open-ended original solutions. And hence, individuals will use their crystalized knowledge as a resource for the mental operation of creativity (Cho et al., 2010). However, Weiss et al. (2020) show that this correlation disappears if originality is nested—as a specific factor—in fluency. The large confidence intervals of the correlation indicate however that further investigations of this relationship are needed.

With respect to the explanatory role of inhibition in the creativity-intelligence relationship, we cannot derive strong conclusions based on the present behavioral data analyses. The results showed that after accounting for individual differences in inhibition, the association between crystallized intelligence and originality decreased to a small magnitude (observed difference of .05), but given the small sample size for latent variable modeling and a single task for inhibition measurement, none of the associations reached statistical significance. Thus, we could not replicate that inhibition explains a significant part of the covariance between intelligence and

creativity. A potential reason might be that the single measurement applied for the inhibition ability was not sensitive enough to capture a broader ability space of inhibition. Thus, for future studies, a broader measurement battery of inhibition should be involved to further explore the multivariate association between creativity, intelligence and cognitive control, going beyond hitherto available studies on this matter (e.g., Benedek et al., 2014). However, psychometric issues in the domain of measuring cognitive control (see e.g., Wilhelm et al. 2013) still need to be solved, before these associations can be comprehensively tested in a latent variable modeling approach.

4.5.3 MSE as a neural marker of inhibition

The MSE results in the Simon task can be interpreted in light of the dynamical system theory of complexity (Stam, 2005), connected with the different levels of control (i.e., proactive and reactive control). The theory assumes that the state space of the signal is limited during visual input as compared to resting brain states with closed eyes (Kaur et al., 2019). In this framework, when individuals are continuously presented with homogeneous stimuli (i.e., non-inhibition/compatible trials), the state space of the dynamical neural system is relaxed. While on the appearance of inhibition/incompatible trials individuals need to apply tonic control over automatic response activation causing the system to be more focused. Therefore, a strong reactive control state would limit the state space manifesting a lower entropy pattern.

Furthermore, MSE in inhibition was reduced across small time scales. The MSE time scales indicate different neural processing levels (McDonough and Nashiro, 2014). Theoretically, small time scales represent local-neural processing and accommodate information about the higher frequency components of neuronal activity, while coarser scales are related to global-neural level processing and slow neuronal oscillations (Courtiol et al., 2016; Grundy et al., 2017; McIntosh et al., 2014; Vakorin et al., 2011). Therefore, different time scales of MSE inform about different neurophysiological mechanisms. Our results indicate that during inhibition the system deals with conflicting information and responds with lower brain signal complexity in local neural networks. In contrast, MSE in non-inhibition is higher because the confrontation with compatible stimuli makes individuals alleviate their control state and disengage from proactive control producing higher complexity patterns. To conclude, MSE is sensitive to the requirements of low and high

control states and therefore, can be considered an effective neural marker of inhibition-related brain states.

4.5.4 MSE in inhibition as a correlate of MSE in verbal creativity

The moderate association between MSE in inhibition with MSE during creative association production as compared to MSE in typical verbal association is in line with the notion that individuals need to inhibit irrelevant responses to create novel as compared with usual ideas. The lower MSE in inhibition trials suggests that the system is more focused and it generates lower complexity signals. Thus, the positive association between MSE in inhibition and in original verbal association production states might represent stable individual differences across multiple states. This means that the inhibition and creativity association needs to be investigated at the level of difference scores (inhibition – non-inhibition and original – typical verbal associations) in future studies.

We also investigated this association at the level of difference scores. However, the MSE in the two contrasted states were highly correlated, leading to psychometric issues with the difference scores, which need to be followed up in future studies. The negative MSE difference score association of inhibition and originality suggests that the more the dynamical neural system focuses to deal with the challenging information input manifesting reduced complexity, the higher complexity it exhibits during creative association production. However, the associations were small and given the current sample size statistically non-significant after multiple test correction. As mentioned, one reason might be that the observed difference scores are poor in their psychometric quality (restricted variance and therefore lack of reliability; see Raykov, 1999; Rogosa & Willett, 1983). Future studies will need to invent study or analyses designs in which difference scores are more variable across individuals. This means, that the correlation of MSE between contrasted neural states need to be minimized by design in the future.

Here we can only conclude that MSE in inhibition is positively associated with MSE in creative neural states up to some extent and this correlation might represent stable individual differences in neural complexity. Our results revealed an association between MSE measures at coarser time

scales mostly at frontal electrodes that were previously shown to be associated with distributed information integration (Grundy et al., 2017). Therefore, the positive relationship between MSE in inhibition and creativity seem to express neural processing at the global level. Thus, given the common involvement of the default mode network, the executive control network, and the prefrontal cortex in creative idea generation and inhibition (Chrysikou et al., 2018), our results align with the literature showing that creative idea generation and inhibitory control encompass wide-spread neuronal networks.

4.5.5 On the relationship between grand-mean MSE in creative and inhibitory neural states and their difference scores with individual differences in gf, gc, fluency, and originality

The present study is the first attempt to explore neural complexity estimates measured in creative and cognitive control neural states as correlates of intelligence and creativity. Our exploration showed that individuals with higher signal complexity in creative and inhibition neural states are better to confirm with requirements of reasoning and with producing fluent and creative associations. Individuals exhibiting higher brain signal complexity during inhibition, thus those who focus their dynamic neural system less, are those with lower gc scores. As shown previously, the grand-mean MSE in original association and inhibition are positively associated. Further, the spatial distribution of grand-mean MSE across the scalp was similar for both MSE in inhibitory and creative neural states. For example, the MSE in inhibition and creative neural states show substantial association with behavioral fluency and originality at temporal, parietal, and occipital scalp locations. Additionally, the magnitude of these correlations were also similar in both neural states. This was also the case for the difference scores of MSE in original vs. typical associations and inhibition vs. non-inhibition. Therefore, the results suggest that both MSE measured during creative and inhibitory neural states have similar pattern of associations with behavioral fluency and originality. The association between MSE in creative neural states with behavioral creativity further demonstrates the convergent validity of MSE as a neural biomarker.

However, the relationship between the MSE difference in inhibition vs. non-inhibition and behavioral creativity and fluency did not support the notion that stronger neural inhibition

facilitates creativity. Thus, we cannot derive support in this regard from the present study. For the behavioral level, Benedek et al. (2014) showed that gf was predicted by updating, but not by other executive functions (i.e., shifting or inhibition). Updating also showed a higher association with creativity as compared to inhibition. There is abundant literature showing that the updating facet of executive abilities is most strongly correlated with intelligence (Ackerman et al., 2005; Friedman et al., 2006), whereas inhibition has much lower associations. Updating and response inhibition have also been linked to creativity (Nusbaum & Silvia, 2011) and fluency and flexibility (Benedek et al., 2012), but not originality. Therefore, the contribution of response inhibition to verbal creativity is less clear even at the behavioral level. Further, here described MSE outcomes of creativity and inhibition also suggest that the neural requirements involved in different types of tasks differentially affect MSE. Therefore, future studies – behavioral and neural complexity related ones – will need to employ a broader measurement of inhibition or in general wider executive functions such as updating and inhibition which are more closely related to intelligence and creativity.

4.6 Conclusions

The present study demonstrated systematic individual differences in the EEG-derived MSE and behavioral performance outcomes providing complementary insights into the neural foundations of the creativity-intelligence-cognitive control relationship. Previous literature demonstrated the power spectrum in the alpha frequency band (or increment in EEG alpha power) to be a robust biomarker of creative ideation (Fink & Benedek, 2014). Our study demonstrates that non-oscillatory properties of the neural signal, such as brain signal complexity measured by MSE deserve additional attention toward a better understanding of the neural foundations of creative mental states. Furthermore, the study suggests that a multivariate approach to the assessed neural states is mandatory, involving for example creative verbal association states, but also inhibitory and fluent mental states. This is because the signal complexity systematically differs across different tasks and association patterns across these mental states need further convergent and discriminant validation aiming to establish non-oscillatory brain signal properties as biomarkers of intelligence and creativity. Even if the present

study was limited by its small sample size, it has the potential to inspire complexity based theories of creativity and intelligence and can guide the design of future multivariate studies.

5 General discussion

The dissertation evaluated a framework for a multimodal creativity assessment and its relationship with intelligence and cognitive control at the neural and behavioral level. Creativity is a coveted trait; by combining HT of creativity (Gabora, 2017) and dynamical systems theory of complexity (Stam, 2005), I parameterized BSC in the EEG signals during performance of a DT task assuming MSE to be a neural marker of creative cognition. Specifically, I predicted that original neural states (MSE during production of original verbal associations) will qualitatively differ in terms of BSC as compared to fluent neural states (MSE during production of typical verbal associations), leading to specific individual differences in MSE. However, prior to examining BSC in creativity, its psychometric properties in terms of reliability had to be investigated. Therefore, Study 1 examined whether MSE can be used as a valid measure and biomarker of individual differences in different brain states (resting and task states).

Overall, **Study 1** reported acceptable reliability of MSE measured across resting and task brain states. The mean level analyses showed that MSE was higher in open eyes resting state than closed eyes and was lowest in the task state at small time scales. At larger time scales, the MSE was the highest in closed eyes condition than open and was consistently lower in the task state. Above the mean level, this differentiation was also possible at the individual difference level. The individual difference analyses revealed that MSE can be established as a trait measure of individuals, above the interindividual variance that is specific for the brain states. Further, MSE as a measure of individual differences is sensitive to task related cognitive processing as compared with resting brain states and hence, the rank order across individuals partly differs in different EEG recording conditions. In sum, MSE quantitatively and qualitatively differed in different measurement conditions. **These results demonstrated that different brain states influence individual differences in BSC which have important implications for Study 2 focusing on the neural mechanisms underlying creativity. The overall gain from Study 1 is that it helped understanding the dimensionality of individual differences in MSE across a magnitude of measurement conditions.** This is relevant for future studies because it showed that some recording conditions in MSE matter, others do not. For example, whereas closed versus open eyes

versus task conditions in general will lead to partly specific rank order of individuals, MSE is not sensitive to task difficulty, stimulus content, and priming – as different conditions of a visual processing experiment (see chapter 2). In the light of these findings, study suggested that future studies should avoid generalizing across measurement conditions when comparing studies on MSE.

Study 2 examined MSE during a DT task performance specifically during production of original and fluent verbal associations. The results demonstrated that MSE was slightly higher in original neural state as compared to fluent neural state. This was the first evidence for MSE to prove as a neural state marker of creative verbal associations. Further, to investigate if and how individuals vary in their rank order in MSE during production of original versus typical associations, I examined the difference between latent means and individual differences in MSE as measured in original versus typical association productions. The results showed that there were slightly above mean level differences in MSE across small and medium time scales but no individual differences in different creative states of the brain. The latent level correlations between MSE estimated in original versus fluent neural states revealed that the two measures are isomorphic with respect to individual differences. In sum, the study demonstrated that creative thinking is characterized by higher BSC across the most time scales of MSE, supporting the idea that complexity of brain activity and creative thinking are related. At the level of individual differences, individuals with higher BSC tended to produce more creative answers when asked to do so, but also produced more conventional answers when asked to name the first verb coming to mind. These results demonstrated a brain basis for a specific aspect of creativity (i.e., verbal creativity) and should be replicated in larger samples and generalized to other creativity tasks.

The explorative **Study 3** broadened the understanding of the relationship between creativity, intelligence, and inhibition from the perspective of BSC. At the behavioral level, the positive creativity-intelligence relationship with respect to their facets (fluency, originality, gf, and gc) was replicated. However, due to small sample size for latent variable modeling, the previous findings according to which inhibition partly explains the relationship between creativity and intelligence could not be extended and replicated. At BSC level, the results demonstrated that MSE in inhibition was specifically associated with MSE in original neural state, but also positively

associated with MSE in fluent neural state. The results indicate that stronger neural inhibition is needed to foster BSC for the generation of more creative associations. Finally, the study explored how MSE acquired in inhibitory and creative neural states are associated with individual differences in gf, gc, fluency, and originality measured with multiple independent behavioral tasks. The MSE in original neural state was substantially associated with gf, fluency, and originality indicating that BSC increases when creative responses are expected to be beneficial for fluency and originality. The association between MSE in creative neural states with behavioral creativity further demonstrated the convergent validity of MSE as a neural biomarker. MSE in inhibition was statistically significantly associated with individual differences in gf and gc, and fluency and originality indicating that less focused neural dynamical activity (higher BSC in inhibition) in cognitive conflict to be detrimental for fluency, originality, and gc scores. In sum, MSE is not only a conclusive neural marker of verbal creativity, but also of inhibition and intelligence. In sum, the study advanced our understanding of the link between facets of creativity and intelligence. The scalp patterns and magnitude of BSC measured in creativity and inhibition and their associations with individual differences in creativity and intelligence provided valuable information for designing future confirmatory studies on BSC approaches to DT and intelligence, using MSE, but also other BSC measures, such as for example non-oscillatory (1/f) signal components (Ouyang et al., 2020). Following, I further discuss the overall results of each study followed by their implications.

5.1 Psychometric quality of MSE in terms of its reliability

The most neuroscientific studies face a general issue of overlooking the strict control for measurement errors (i.e., unreliability). **The first general aim of the dissertation was addressed by Study 1 which provided comprehensive reliability estimates of MSE in different brain states.** By using a multivariate approach (in this dissertation, each MSE analyses used multiple data segments (or epochs) of the EEG signal captured at the same electrode for multiple conditions) including repeated measurements of interest, SEM was used to capture the 1) true score, referring to the variance of the latent variable, 2) method or content specificity, here represented by the variance across individuals that is due, for example, to different task or resting

state conditions in which MSE was measured, and 3) the measurement error or unreliability. Other general linear modeling techniques such as ANOVA systematically compare groups with randomly assigned members that correspond to levels of independent and dependent variables. Therefore, such measures do not strictly control measurement errors and hence, sacrifice reliability. In contrast, SEM allows an individual level of analysis that involves greater recognition of reliability and validity of the observed scores. Thus, SEM was implemented to all of the three studies strictly controlling for the measurement error and hence, providing an excellent estimate for reliability.

In **Study 1**, the measurement models defined for resting and task brain states explored the reliability of MSE values across the whole scalp and for multiple time scales (1-10) showing higher reliability across the scalp in lower time scales in all experimental conditions. The reliability was also revealed by the estimated high latent level correlations between MSE in different brain states (see section 2.5.6 in chapter 2). Therefore, the study provided evidence suggesting that MSE is a valid measure of individual differences and can be reliably measured across different brain states. Further, the reliability was satisfactory across different conditions but varied across the MSE time scales. Thus, the study established MSE complexity measures as reliable indicators of individual differences in resting and task brain states. The results suggested that it is relevant to have comprehensive reliability estimates before designing studies that relate MSE with cognitive performance because reliability places an upper limit on validity. The results served as methodological recommendations for future individual differences research on MSE–cognition in which it will be important to recognize that reliability decreases across increasing temporal scales but is still acceptable and is highest in resting state measurement conditions of the EEG.

5.2 Observed–level MSE in resting state and task brain state

Study 1 and **2** assessed MSE in resting state and during performance of a specific task. The reason for including resting state data above task based data into our studies was because the brain is intermittently active and displays spatiotemporally structured dynamics also in states with no direct task processing (Sleimen-Malkoun et al., 2015). Further, the resting-state brain activity represents baseline activations which are not specific due to any external task. The observed level results of MSE in resting state in Study 1 were replicated in Study 2. Figure 5.1

illustrates grand-mean MSE across 10 time scales for closed and open eyes and task processing brain state (FaHPF; face processing in the difficult task condition for familiar faces in a primed condition) from Study 1 and during creative idea production in a DT task (original associations production) from Study 2 at Fz and Cz electrodes respectively. Although the tasks, pre-processing of the EEG signals can't be directly compared as the EEG recording parameters and pre-processing steps differed in both studies. However, it is of interest to compare the overall results indicating that observed level MSE is consistently higher in closed eyes as compared to open eyes at medium and higher time scales (6-10). Further, the MSE during task processing brain state in Study 1 was consistently lower as compared to the resting state across the scalp and time scales. In **Study 2**, the similar pattern was overserved; MSE was higher in closed eyes as compared to the open eyes and was lowest in the DT task across the scalp. However, the differences between closed and open eyes was rather small on average across individuals in both studies.

These findings are in line with the dynamical systems theory of complexity (Stam, 2005) that assumes the state space of the signal to be most widely explored in the closed eyes condition. The brain is a nested network of coupled dynamical systems (Stam, 2005). At rest, those nested networks of constantly interacting dynamical systems are characterized by a weak level of synchronization. The resting state brain displays complex spatiotemporally structured dynamics in which neural networks are intermittently activated. In this case MSE captures the spontaneous cortical dynamics in the resting state EEG that are unconstrained by external inputs or tasks manifesting high entropy. More concretely, mental activity at rest is self-organized by the underlying complex neural network and is not strongly constrained by structured external stimulations. Therefore, the brain's dynamical activity can freely explore a vast state space supported by the underlying neural network. Thus, the signal is diverse and highly complex in resting state condition (Allen et al., 2014).

During task processing brain state, the interplay with visual input stimulus and related differentiation of neural networks during processing limits the state space of the signal. The system is more focused towards stimuli and thus, nested networks of the brain are characterized by high levels of synchronization. Therefore, during task processing state, the brain's dynamic

state space is constrained and limited by the stimuli that make the system be more focused. This results in decreased BSC as compared with non-constrained (resting) brain states. Specifically, during processing of the task, the MSE captures the higher synchronized cortical dynamics generating patterns of lower complexity. Following the same argument, resting state with open eyes also imposes constraints on the brain states, thus corresponding to lower MSE in a range of scales when compared to the eye closed condition. However, the unstructured visual inputs (i.e., a fixation cross) in open eyes resting state could induce additional fluctuations in the neural signals.

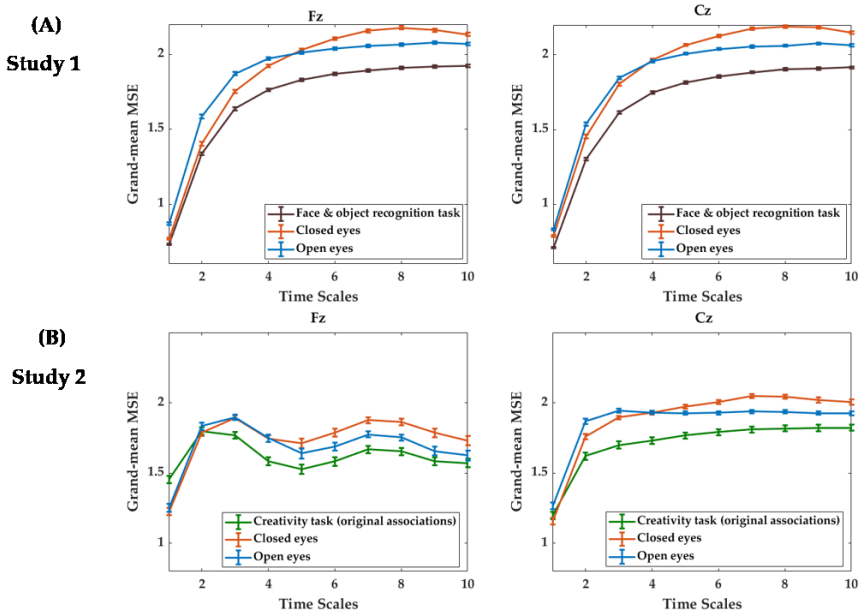

Figure 5.1. Grand-mean MSE in resting state closed and open eyes and during specific task performance in study 1 and 2. (a) MSE in resting state and during performance of a face and object recognition task showing MSE is higher in closed eyes as compared to opened eyes and during task performance across higher time scales (6-10). (b) MSE in resting state (open and closed eyes) and during performance of a verbal creativity task (DT task) in which individuals produced original verbal associations replicating results of Study 1 showing higher MSE in closed as compared to opened eyes and during task performance in higher time scales.

The three studies further compared the MSE between different task conditions. Figure 5.2 depicts the grand-mean MSE in task and resting brain state (Study 1), during productions of original and typical verbal associations (Study 2), and in inhibition and non-inhibition conditions (Study 3). In **Study 1**, the grand-mean MSE in different task conditions did not show any substantial differences. **Study 2** showed that MSE during production of original verbal association was slightly higher as compared to the MSE during production of typical verbal association. However, the difference between the conditions was small and statistically non-significant. Based

on the HT of creativity and dynamical systems theory of complexity, the results were in line with our expectation showing higher MSE during production of original verbal associations as compared to the production of typical verbal associations. The results indicate that the brain activity becomes more complex when producing creative ideas. Further, in light of these findings MSE can be considered as a sensitive state marker of creativity as it differentiates between diverse states of idea generation: fluent versus creative. Nevertheless, these results demonstrate a brain basis for a specific aspect of creativity (verbal creativity) using MSE.

Study 3 showed higher MSE in non-inhibition (compatible trials) as compared to the MSE in inhibition (non-compatible trials). In light of dynamical systems theory of complexity, the different levels of control (i.e., proactive during non-inhibition trials and reactive control during inhibition trials) may have caused the different BSC. As demonstrated in Study 1, the state space of the signal is limited during visual input as compared to resting brain states with closed eyes (Kaur et al., 2019). In a similar vein, during continuous presentation of homogenous compatible trials, the state space of the dynamical neural system is relaxed exhibiting higher MSE. In contrast, during presentation of incompatible trials, individuals apply tonic control over automatic response activation, causing the neural system to be more focused. Therefore, a strong reactive control state would limit the state space manifesting a lower entropy pattern. Further, the MSE difference between two conditions of cognitive control was statistically substantial at small time scales. The MSE time scales indicate different neural processing levels (McDonough & Nashiro, 2014). Theoretically, small time scales represent local neural processing. They accommodate information about the higher frequency components of neural activity. Coarser/higher scales are related to global network-level processing and slow neuronal oscillations (Courtiol et al., 2016 ; Grundy et al., 2017; McIntosh et al., 2014; Vakorin et al., 2011). Different time scales of MSE inform about different neuro physiological mechanisms. Therefore, the dynamical neural system becomes locally more focused to deal with challenging information input (conflict as compared with non-conflict trials) and responds with lower BSC in local neural networks as indicated by the small time scales of MSE. In summary, external stimuli during the task processing state transfer the state of the dynamic brain system from non-directed mind wandering to being focused on the tasks. Similarly, in open eyes resting state where individuals are focused on a fixation cross, the

state of the system is focused. However, in this condition, slight mind-wandering is possible, reducing the BSC as compared to closed eyes resting state.

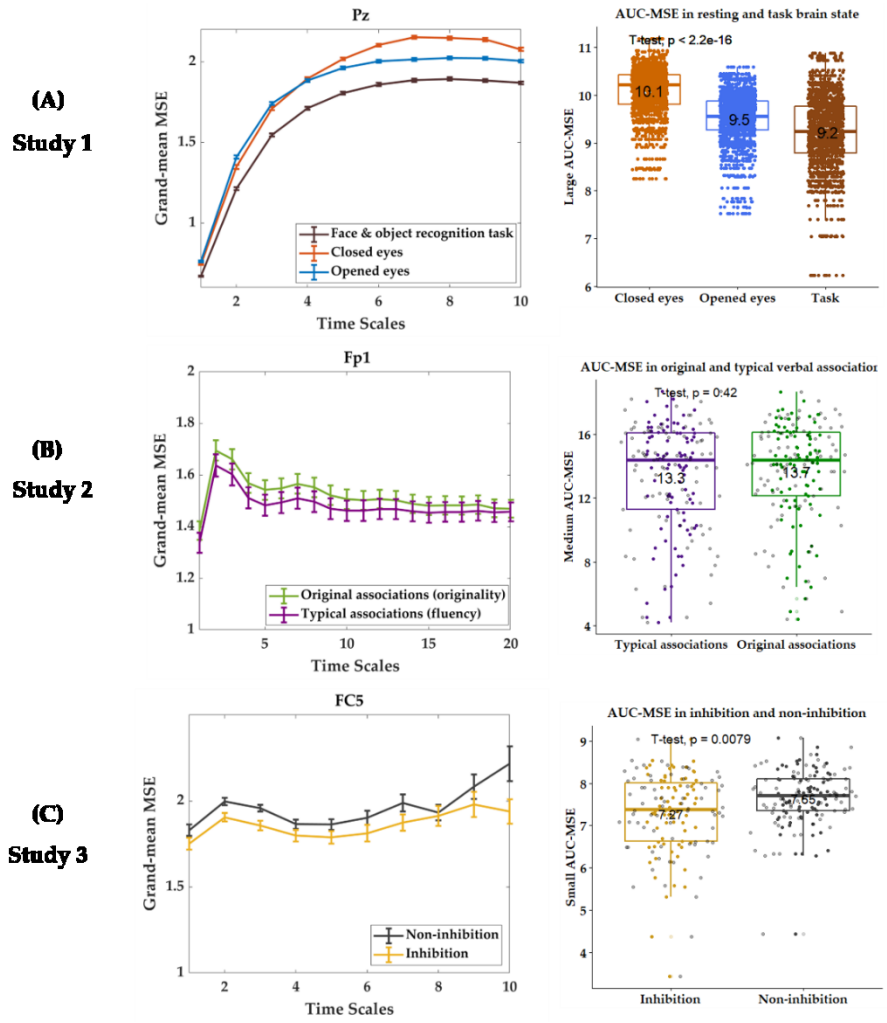

Figure 5.2. Illustration of the observed-level MSE computed in the three studies. The left side of Panel (a) shows line plots of grand-mean MSE at Pz electrode across 1-10 time scales in Study 1. The right side shows the mean difference calculated using t-test in the average Area Under the Curve(AUC) scores of MSE integrated across large time scales (6-10). The results show that average MSE is higher in closed eyes condition than in open eyes and is the lowest during the face and object recognition task performance. The left side of panel (b) illustrates grand-mean MSE calculated in typical (fluent) and original associations (original) in the verbal divergent thinking task at Fp1 electrode across 1-20 time scales in Study 2. The right side shows the mean difference in the AUC scores of MSE integrated at medium time scales (6-10) between the two conditions. The results show that there was no substantial difference in MSE between typical versus original verbal associations productions. The left side of panel (c) shows the grand-mean MSE measured during a cognitive control task in inhibition and non-inhibition condition across 1-10 time scales in Study 3. The right side plot shows the mean difference in the AUC scores of the MSE integrated across small times scales (1-5) showing the difference was statistically substantial.

5.3 Individual differences in MSE measured in resting and different task brain states

Literature has shown that resting state conditions affect the reliability and consistency of brain activity (Patriat et al., 2013). There is a discussion and a main stream opinion in the literature to use only one of these conditions for resting state fMRI. For example, resting state fMRI studies have indicated that the strength and reliability of functional connectivity is lower for the open eyes as compared to closed eyes condition (Feige et al., 2005; Patriat et al., 2013). However, the individual differences analyses in MSE in different resting conditions in Study 1 showed that the specificity of MSE measured in open versus closed eyes explained a significant proportion of inter-individual variance over the general factor of resting state MSE. The results indicated that individual differences in MSE across the scalp and different time scales are specific in the open and closed eyes conditions. This means that the complexity of brain states in individuals is specifically affected by the resting state conditions whether eyes are closed or open. Precisely, the results suggested that the rank order of individuals for MSE at rest with closed versus open eyes is not completely overlapping because there is a qualitative difference between the two recording conditions. Thus, the two conditions could serve as separate predictors for different aspects of cognitive abilities and their disorders.

Further, the investigation of specific variance due to each experimental condition in the task state MSE showed that not only the grand-mean MSE is different across experimental task conditions, but also individuals systematically vary depending on which experimental task condition the MSE was measured in. However, not all task conditions are influential on MSE. Whereas stimulus content, task difficulty (as manipulated by long-term memory load) and priming did not differentially impact MSE, individual differences were specifically affected by novel (unfamiliar) relative to familiar stimuli. Figure 5.3 shows the two factor model (MSE in general task state and additional factor accounting for individual differences in unfamiliarity specific MSE) which has been shown to be a better description of the individual differences in the task processing MSE than the one factor model (only MSE in general task state). Thus, the novelty of a stimulus differentially impacted the BSC across individuals. This finding is invariant across temporal scales and spatial locations distributed across the scalp. Therefore, there might still be

systematic individual differences in MSE depending on experimental conditions if some individuals tend to have a positive and other a negative difference, leading to no mean difference in average but substantial variation across individuals. However, arguably such patterns are difficult to interpret. Thus, the impact of stimulus novelty on individual differences in BSC is thus, was only partly in line with our findings in open eyes resting state in terms of dynamical systems theory of complexity. When the brain is confronted with a new stimulus, it will switch to be more focused on a novel response state as compared with previously learned stimuli, leading to limiting the state space of its signal output, manifested by reduced MSE. However, this only happens in some individuals, whereas the same amount of individuals exhibited the opposite trend. This is arguably a finding that needs to be addressed systematically in future research. Thus, MSE specificity in terms of individual differences imply that the relationship with cognitive outcomes on the behavioral level may depend on the specific MSE measurement conditions within a given task. Therefore, future studies focusing on MSE-cognition will need to systematically vary MSE measurement conditions and obtain a comprehensive picture on how the MSE–cognition relationships depend on the task state in which BSC is estimated.

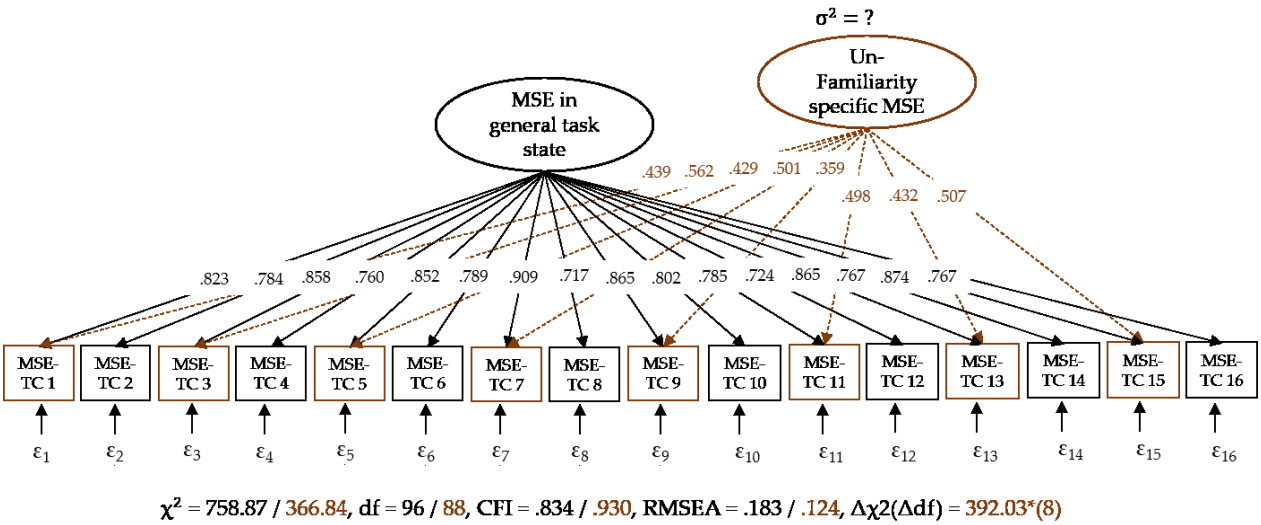

Figure 5.3. Schematic representation of the two latent factor SEMs (one general factor: MSE in general task state) and second one nested under the general factor in first study: Un-familiarity specific MSE) for electrode T7 and time scale 5. MSE TC – MSE calculated in the Task Condition (the numbers represent the 16 experimental conditions defined by the combinations of the four factors: Content [Face vs. House]; Difficulty [Difficult vs. Easy]; Unfamiliarity [Unfamiliar vs. Familiar]; Priming [Primed vs. Unprimed]).

In **Study 2**, the investigation of individual differences in MSE during production of typical and original associations showed that individuals did not systematically vary in MSE in different

verbal creative conditions. There was no specificity. Further, the latent level correlation between MSE in originality and MSE in fluency was high indicating that individuals with higher BSC during original association production also show higher BSC during typical verbal association productions. In other words, the MSE estimated during productions of original and fluent verbal associations are isomorphic with respect to individual differences. Therefore, rank order of individuals is indistinguishable between the two conditions and hence are overlapping. A possible explanation might be that individuals with rich lexicons produce highly original verbs as well as conventional verbal associations. Therefore, such individuals will have high BSC difference between the original versus typical verbal associations as compared to individuals with poor lexicon, as they will produce less original as well as conventional verbal associations.

Study 3 showed that individuals with higher BSC in creative and inhibitiory neural states are better at reasoning ability and producing fluent and creative verbal associations. Further, the results suggested that individuals exhibiting higher BSC during inhibition and productions of creative verbal associations, focus their state space of the neural system less, generating higher patterns of entropy. Additionally, the grand-mean MSE in productions of creative verbal associations and MSE in inhibition were moderately associated. These results are in line with the notion that individuals need to inhibit irrelevant responses to create novel as compared with usual ideas (Benedek et al., 2012; Camarda et al., 2018; Zabelina & Ganis, 2018). The verbs generated during the verbal creativity task (used in Study 2 & 3) has been shown to be associated with higher cognitive load (Abdullaev & Posner, 1998; Snyder et al., 1995). Therefore, the results confirm with the existing literature showing that creative verb generation induces high cognitive load.

The spatial distribution of grand-mean MSE in creative and inhibitory neural states across the scalp and the magnitude of their correlations with behavior estimates of fluency and originality were similar. This was also the case for the difference scores of MSE in original versus typical associations and inhibition versus non-inhibition. Therefore, the results suggest that both MSE measured during creative and inhibitory neural states have similar pattern of associations with behavioral fluency and originality. In sum, Study 3 extended the understanding of the creativity-intelligence-inhibition relationship at the level of BSC measured by MSE demonstrating common

and differential involvement of inhibition in fluency and originality, as well as replicating the moderate relationship between intelligence and creativity extended to their facets.

5.4 Dimensionality of creativity measured by divergent thinking

DT measures are frequently applied to measure creativity. However, there are only few studies that have focused on dimensions of DT such as fluency and originality. **Study 2 showed high correlations at the latent level between MSE in originality and fluency conditions of a DT task. This indicated that participants' individual MSE was not different across the two conditions.** This pattern was replicated at the behavior level in **Study 3** that included the behavioral DT data collected in a multivariate study and partially analyzed in a combined study by Weiss et al. (2020). **Findings showed that fluency and originality, despite being conceptually different aspects of DT, are highly associated even if measured by independent tests (e.g., Silvia, 2008).** The results are also in line with the literature which have indicated their relationship to be significantly positive (Dumas & Dunbar 2014; Runco 2010; Silvia 2008) postulating that individuals who are highly fluent are also likely to be original. Theoretically, fluency is a necessary precondition for originality (e.g. Acar et al., 2017). A possible explanation for the highly correlated MSE values in fluency and originality is that original and typical associations cues tap into the lexical system of the brain. An individual with a rich vocabulary will produce highly fluent as well as highly original associations. Similarly, at the behavioral level, individuals need to first produce a sufficient quantity of ideas i.e., fluent idea generation, to come up with an original solution. Therefore, individuals who are fluent will also be original, resulting in high correlations between the two facets of DT.

Another possible explanation lies within the experimental task design of the MSE measurement. In Study 2, the trials were presented intermittingly, possibly blurring any differences between the conditions. This is because the participants produced fluent and original associations within short trials, and MSE might not be sensitive enough to capture such trial level differences in two such closed coupled facets. Future studies could investigate whether a blocked experimental design would allow to carve out the true differentiation and correlation between the two.

5.5 Conclusions

The present dissertation provides new insights into MSE as a neural biomarker of creativity. In reference to the specific aims of the dissertation formulated earlier, I will now condense the most important findings from all three studies into a brief summary and conclusions:

- Aim 1: Reliability of MSE−MSE is a reliable measure of individual differences in resting state with closed and open eyes and task state.
- Aim 2: Grand-mean MSE in different brain states–Wandering neural system in closed eyes and creative thinking is characterized by higher BSC. Inhibition and resting state open eyes are characterized by focused neural system leading to lower BSC.
- Aim 3: Individual differences in MSE in different brain states−Individuals differences are specific and follow different rank order in MSE measured in closed, open eyes, and task state but not in MSE in fluency and originality.
- Aim 4: MSE as a neural marker–MSE is a sensitive neural marker of verbal creativity, inhibition, and intelligence.

The overall results demonstrated that MSE does not only provides a summary of the neural dynamics across multiple time scales but also captures inter-individual trait-like differences in different brain states. The results showing that BSC and creative thinking are related, offer the perspective to enhance creative thinking by suitable brain stimulation or neurofeedback interventions. The findings demonstrating systematic individual differences in the MSE provided complementary insights into the neural foundations of the creativity-intelligence-inhibition relationship. These findings suggest that a multivariate approach to the assessed neural states is mandatory, involving for example creative verbal association states, but also inhibitory and fluent mental states. This is because BSC systematically differs across different tasks and association patterns across these mental states need further convergent and discriminant validation aiming to establish non-oscillatory brain signal properties as biomarkers of creativity, inhibition, and intelligence.

In sum, this dissertation took a leap from analyses of traditional measures of the regular and predictable signals like ERPs and investigated the irregularity in the EEG signals. Further,

previous literature has demonstrated the power spectrum in the alpha frequency band (or increment in EEG alpha power) to be a robust biomarker of creative ideation (Fink & Benedek, 2014). MSE is one of the most widely used temporal complexity measure that extracts non-oscillatory properties of the neural signals among many other existing measures such as non-oscillatory (1/f) signal components (see Ouyang et al., 2020). These measures do not account for simple regular oscillations but rather, irregularity in the time series. Therefore, BSC estimated by MSE can also be used as a robust biomarker for abilities such as creativity, inhibition, and intelligence. One might ask, "what are the physiological mechanism of the BSC?" This question has been answered in a study by Wang et al. (2018) which investigated the relationship between the resting state fMRI and functional connectivity. The findings showed that higher the complexity of the regional neural activity is, higher is the functional connectivity of this region is with other brain regions. The results indicate that regional neural complexity and functional connectivity could be two aspects of brain's information processing showing increased complexity as higher information processing. In this framework, BSC can be served as an index of brain's capacity of information processing.

To conclude, the dissertation provides an alternate computational approach using MSE for extracting the fundamental features of the human brain showing that MSE can be used as a potential biomarker for complex brain functions. The non-oscillatory properties of the neural signal measured by MSE deserve additional attention toward a better understanding of the neural foundations of creative as well as other normal healthy mental states.

5.6 Limitations

Creativity is a challenging and complex construct in cognitive and neuroscience to investigate. However, the dissertation made an attempt by combining complexity related theories in psychology and physics in Study 2 and expected a larger difference between MSE in original versus typical verbal associations productions. However, the difference was small and statistically not substantial. The possible explanation at the hand is that MSE might be not be sensitive enough to capture the differences between such closely intertwined facets of creativity i.e., fluency and originality. Additionally, during verbal associations productions, these close creative abilities should probably be rapidly shifting back and forth and hence are inseparable when larger swaths

of time are considered such as in MSE analyses. Further, the DT task only taps into one aspect of creativity i.e., verbal creativity. Therefore, for future studies aiming to investigate individual differences in BSC of creativity need to implement a paradigm which would first taps into multiple facets of creativity such as fluency, flexibility, and originality. Further, in Study 3, due to small sample size for latent variable modeling, previous findings could not be replicated according to which inhibition party explains the relationship between creativity and intelligence. To conclude, MSE is a potential marker of creative verbal association and inhibitory related neural states, but replications and extensions in a larger sample are needed, especially with respect to the brain-behavior relationships.

5.7 Future directions

The standard definition of creativity is outcome focused. The definition is used by researchers to analyses different facets of creativity in the process. However, to produce creative ideas, individuals usually start with fluent idea generations, then moving on to inhibit irrelevant responses to create novel ideas. In the next step, ideas that are worthy of exploration, are then approved by executive control processes (Beaty, 2020). Therefore, creativity involves many interacting processes by large scale brain networks working together (Beaty et al., 2019). The processes cannot be easily inferred from outcomes. Thus, future studies should focus on creativity as a process and not as an end product.

The MSE results of the three studies are smeared representation of the BSC because of limited spatial resolution of the EEG. For example, as demonstrated in first study, MSE and its reliability are spatially distributed and specifically modified by tasks, suggesting that different brain systems may have different spatio-temporal complexity. This means that individuals with similar MSE patterns could still have different states in the high dimensional space as the complex spatio-temporal patterns in the brain represent the high dimensional space. As brain activity is characterized by spatio-temporal complex patterns. Spatial coherence (functional connectivity) has been used to study the relevance of brain activity in brain functions. Due to limitations in spatial resolution, the focused has been shifted towards temporal resolution. However, due to limited spatial resolution, it is still an open question how the different scales of MSE reflect the

spatiotemporal complexity. Therefore, future studies can combine technologies such as fMRI-EEG co-registration with both high spatial and temporal resolution that could help to provide a comprehensive characterization.

Furthermore, recently proposed methods for explicit identification of multivariate patterns in neural data (Fahrenfort et al., 2018; Haxby et al., 2001) could be combined with entropy estimates in the future. The aim would be to measure the transition among the identified multivariate patterns as a potential marker to quantify the spatiotemporal switching of the dynamical patterns, which may allow better differentiating creative versus less-creative states.

Another critical but overlooked issue in non-linear analysis of brain signal dynamics is the choice of parameters in these non-linear methods. For example, in the MSE analyses the choice of the pattern length (*m)* and threshold (*r)* is still an open setting. A study by Yang et al. (2018) illustrated a general strategy for selecting entropy parameters to reduce bias entropy estimates but in resting state fMRI signals. Another issue in MSE calculation is that *r* is not equally liberal across all time scales because it is used as *r*SD* of the original time series. The signal during MSE analysis is successively coarse-grained at different time scales, except scale 1, which is similar to low-pass filtering. But the *r* is calculated only relative to the *SD* of the original, unfiltered signal (at time scale 1). However, successive coarse-graining reduces the *SD* of the signal and as a result signal variance is normalized which introduces biased entropy estimation if it is calculated with a constant *r* (Kosciessa et al., 2020). Further, the traditional interpretation of MSE time scales based upon direct scale-to-frequency mapping has been challenged (i.e., at smaller time scales, MSE mainly reflects fast and local neural activities, whereas at larger scales MSE mainly captures slow dynamics across broader spatial domains). A study by Kosciessa et al. (2020) suggests to compute the similarity bounds for each scale factor i.e., scale-wise *r* MSE analysis. Following these suggestions, in Study 2, I performed global similarity bounds or scale-wise *r* MSE analysis. The results are provided in the supplementary material of Study 3. They reveal that the traditional MSE and scale-wise *r* MSE did not considerably differ. Therefore, multivariate analyses reported in the three studies of the dissertation are based upon traditional MSE analyses using invariant-*r* (or global similarity bound). However, future studies focusing on EEG-MSE analyses should implement a systematic exploration for the choice of the optimal parameter settings and provide

recommended settings. Future studies focusing on BSC analyses of creative cognition should systematically explore the longitudinal changes in the neural dynamics of creativity focusing not only verbal creativity but can be implemented to understudied domain: *scientific creativity*.

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APPENDIX

APPENDIX A – Supplementary Material of Study 1

Appendix A1 – Topographical plots of grand mean MSE in resting state closed and open eyes and task state for time scales 1-10

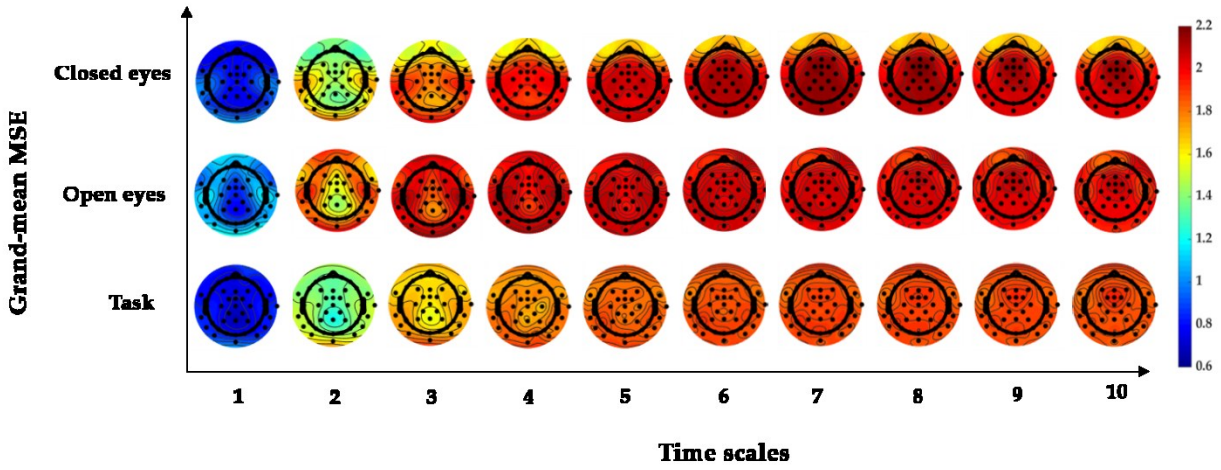
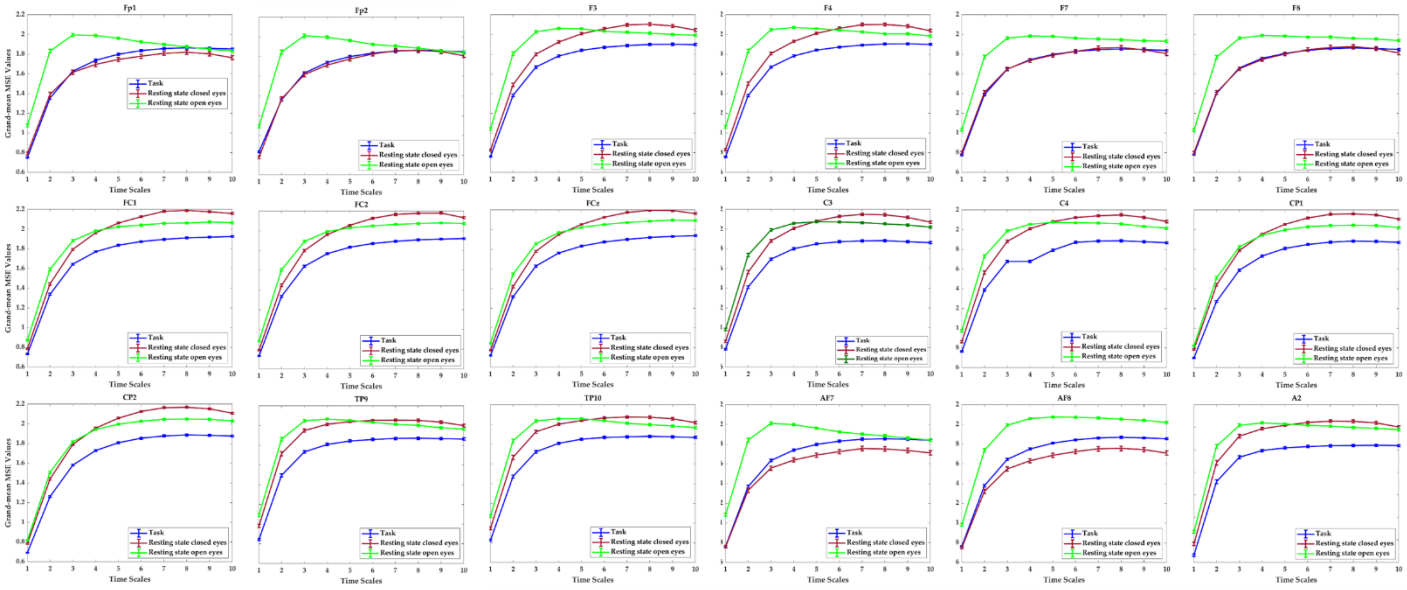


Figure A1. Scalp topographies of grand-mean MSE in different recording conditions of EEG signals across 10 time scales. First top row represents closed eyes, second row represents open eyes resting state, and the last bottom row shows task processing condition (averaged over 16 TCs), respectively. Dark red color on the scalp topologies represent large MSE values and dark blue color shows small values.

Appendix A2 – Line plots grand mean MSE in resting state closed and open eyes and task state across time scales 1-10



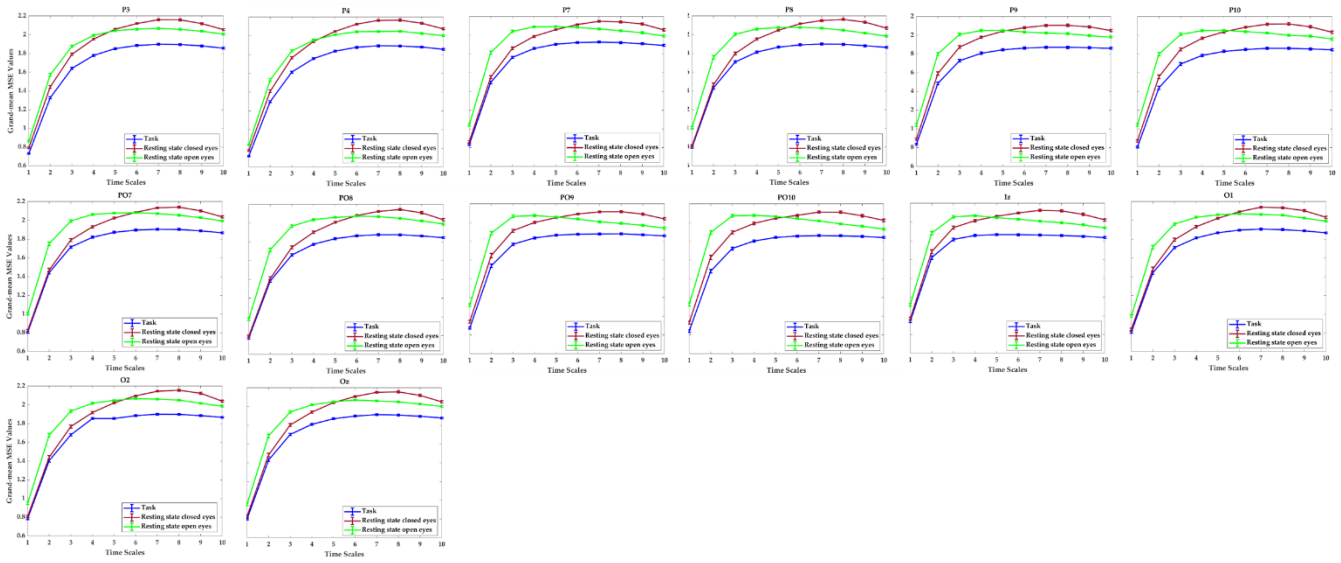


Figure A2. Line plots of grand-mean MSE with error bars (standard error of the mean are calculated across participants and across 16 TCs) at for rest of the electrodes and time scales 1–10, differentiated for three recording conditions in which EEG signals were recorded.

Appendix A3 – Topographical plots of MSE reliability estimates in resting state closed and open eyes and task processing condition for time scales 1-10

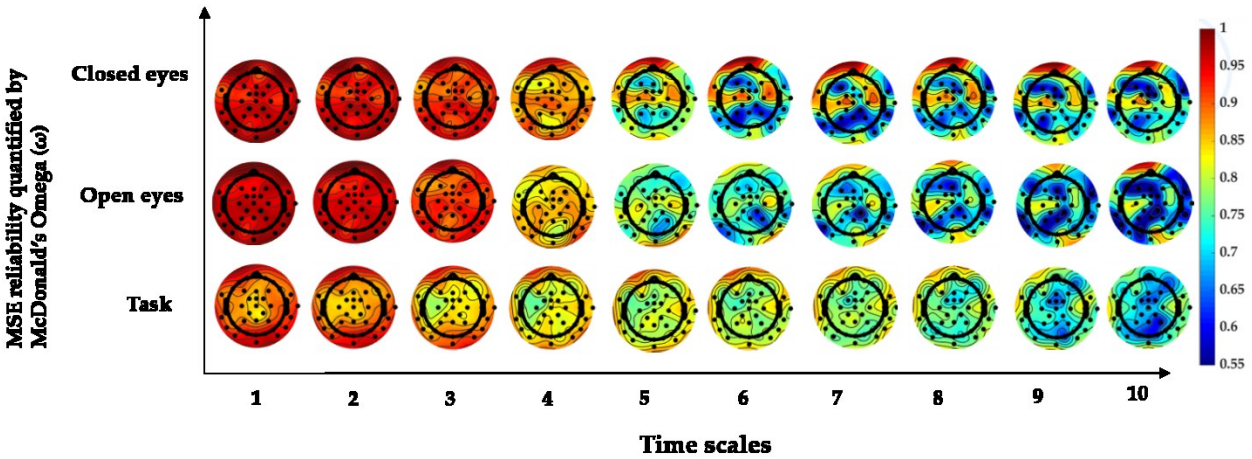


Figure A3. Scalp topographies of MSE reliability estimates in different recording conditions of EEG signals across 10 time scales. First top row represents closed eyes, second row represents open eyes resting state, and the last bottom row shows task processing condition 1 FaHPF (face processing in the difficult task condition for familiar faces in primed condition), respectively.

APPENDIX B – Supplementary Material of Study 2

https://www.frontiersin.org/articles/10.3389/fnbeh.2020.00146/full#supplementary-material

APPENDIX C – Supplementary Material of Study 3

https://osf.io/sg9e2/

Confirmation of Authors' Contributions

I hereby confirm that Yadwinder Kaur contributed to the aforementioned studies as stated below:

Article 1: **Kaur, Y.**, Ouyang, G., Junge, M., Sommer, W., Liu, M., Zhou, C., & Hildebrandt, A. (2019). The reliability and psychometric structure of Multi-Scale Entropy measured from EEG signals at rest and during face and object recognition tasks. *Journal of neuroscience methods*, *326*, 108343. https://doi.org/10.1016/j.jneumeth.2019.108343

Contributions: Yadwinder Kaur, Andrea Hildebrandt, Werner Sommer, and Changsong Zhou designed the study and the conception of the research questions. Yadwinder Kaur carried out the data analysis and prepared the first draft of the paper. Werner Sommer supervised the EEG data processing and analysis. Guang Ouyang and Changsong Zhou guided the MSE analysis. Andrea Hildebrandt and Matrin Junge supervised SEM analysis and their interpretation. Mianxin Liu assisted in AUC analysis. Andrea Hildebrandt, Werner Sommer, and Chagsong Zhou guided the study design, structure of the paper, and results interpretation. All co-authors were involved in the editing of the manuscript at several stages.

Article 2: **Kaur, Y.**, Ouyang, G., Sommer, W., Weiss, S., Zhou, C., & Hildebrandt, A. (2020). What does temporal brain signal complexity reveal about verbal creativity?. *Frontiers in behavioral neuroscience*, *14*. https://doi.org/10.3389/fnbeh.2020.00146

Contributions: Yadwinder Kaur and Andrea Hildebrandt conceptualized the study. Yadwinder Kaur designed it, collected the data, which she independently preprocessed and analyzed, discussed results with all co-authors, and drafted the manuscript. Andrea Hildebrandt and Werner Sommer supervised the task design and the EEG data acquisition, processing and statistical analysis, and results interpretation and theoretical discussion. Guang Ouyang and Changsong Zhou supervised the MSE analysis and contributed to the interpretation of results. Selina Weiss contributed to the behavioral data collection and analysis. All co-authors were involved in the editing of the manuscript at several stages.

Article 3: **Kaur, Y.**, Weiss, S., Zhou, C., Fischer, R., & Hildebrandt, A. (2021). Exploring Neural Signal Complexity as a Potential Link between Creative Thinking, Intelligence, and Cognitive Control. *Journal of Intelligence*, *9*(4), 59. https://doi.org/10.3390/jintelligence9040059

Contributions: Yadwinder Kaur and Andrea Hildebrandt conceptualized the study. Yadwinder Kaur collected, pre-processed, and analyzed the EEG and the behavioral data. Andrea Hildebrandt guided in data analysis and interpretation of the results and helped to write the paper. Chagsong Zhou guided the MSE analysis and theoretical discussion. Selina Weiss cleaned, processed, and scored the behavioral data. Rico Fischer guided the Simon data analysis and interpretation of results. All co-authors were involved in the editing of the manuscript at several stages.

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Prof. Dr. Andrea Hildebrandt

Declaration of originality (Eigenstandigkeitserklärung)

I confirm that I completed the work independently and used only the indicated resources. This dissertation is my own work. All the sources of information have been acknowledged by means of references.

This dissertation has, neither as a whole, nor in part, been submitted for assessment in a doctoral procedure at another university.

This is to confirm that I confirm that I am aware of the guidelines of good scientific practice of the Carl von Ossietzky University Oldenburg and that I adhered to them.

This is to confirm that I did not use any commercial placement or consulting services in connection with my promotion procedure.

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Academic positions

Since 04/2021	Scientific Researcher at the Department of Psychology, for the development of a serious game for statistics, Carl von Ossietzky University of Oldenburg
10/2018 – 03/2020	Scientific Researcher at the Department of Psychology, division for Methods and Statistics, Carl von Ossietzky University of Oldenburg
03/2016 – 09/2018	Scientific Researcher (Scholarship holder) at the Institute of Psychology, chair Personality Psychology / Psychological Assessment, University of Greifswald
01/2016 – 03/2016	Visiting Scientific Researcher at the Department of Psychology, research group Biological Psychology / Psychophysiology, Humboldt University of Berlin

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Professional experience

07/2020 – 09/2020	Freelance data analyst at the University of Applied Sciences Potsdam, Potsdam, Germany

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Education

Since 03/2016	PhD student (supervised by Prof. Dr. Andrea Hildebrandt)
07/2009 – 04/2015	Integrated Bachelor of Technology (B.Tech.) in Converging Technologies and Master of Technology (M.Tech.) in Cognitive and Neuroscience at the Center for Converging Technologies, University of Rajasthan, Jaipur, India

08/2014 – 11/2014	Master's dissertation on "Design of Computerized Central Executive Function Tasks of Updating Manipulation and Dual Task Coordination: An Event-related Potential study" at the Neuropsychology Department of National Institute of Mental Health and Neurosciences, Bangalore, India
08/2014 – 11/2014	Bachelor's dissertation on "Cognitive Assessment and Enhancement Using Action Video Games (Multiplayer)" at the department of Bio-Medical Engineering, Institute of Nuclear Medicine and Allied Sciences, Defence Research and Development Organization, Delhi, India

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Scholarships

03/2016 – 08/2018	Landesgraduiertenförderung Mecklenburg-Vorpommern (LGF M-V) state scholarship at the University of Greifswald

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Publications

Kaur, Y., Ouyang, G., Junge, M., Sommer, W., Liu, M., Zhou, C., & Hildebrandt, A. (2019). The reliability and psychometric structure of Multi-Scale Entropy measured from EEG signals at rest and during face and object recognition tasks. *Journal of neuroscience methods*, *326*, 108343. https://doi.org/10.1016/j.jneumeth.2019.108343

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Li, X., **Kaur, Y.**, Wilhelm, O., Reuter, M., Montag, C., Sommer, W., Zhou, C., & Hildebrandt, A. (2020). Resting state brain signal complexity of young healthy adults reflects genetic risk for developing Alzheimer's Disease. *BioRxiv*, 2020.11.08.373167. https://doi.org/10.1101/2020.11.08.373167

Conferences

Kaur, Y., Ouyang, G., Zhou, C., & Hildebrandt, A. (July, 2018). *Exploring the neural correlates of creativity via Multi-Scale Entropy measures of the brain signal.* Talk at the 19th European Conference on Personality (ECP) as a part of symposia organized by Hildebrandt, A., Individual Differences in Creativity – Measurement, Scoring, Structure and Nomological Net, Zadar, Croatia

Kaur, Y., Ouyang, G., Zhou, C., & Hildebrandt, A. (September 2018). *Brain signal complexity and divergent thinking*. Talk at the 51st Conference of the German Psychological Association (German: Kongress der Deutschen Gesellschaft für Psychologie) as a part of symposia organized by Weiss S. & Hildebrandt, A., Creative Abilities: Measurement, Scoring, and Nomological Net including Genetic, Neurophysiologic, and Behavioral Levels, Frankfurt, Germany

Further Presentations

Kaur, Y., Ouyang, Q., Sommer, W., (June 2016). First PhD oral presentation on *Multi-Scale Entropy Analysis of EEG signals* at Colloquium of the Department of Biological Psychology division of Department of Psychology, of Prof. Dr. Werner Sommer at the Humboldt Universität zu Berlin, Berlin

Kaur, **Y.**, Ouyang, Q., Junge, M., Sommer, W., Liu, M., Zhou, C. & Hildebrandt, A. (July 2017). Oral presentation on *Exploring the reliability and structure of Multi-Scale Entropy measures from EEG signals – Comparing signals recorded at rest versus during processing Face and Object Recognition task* at Germany-Hong Kong Joint Workshop, Hong Kong Baptist University, Hong Kong

Kaur, Y., Ouyang, Q., Zhou, C. & Hildebrandt, A. (September 2018). Oral presentation on *Individual differences in divergent thinking measured via Multi-Scale Entropy(MSE)* with research group of Prof. Dr. Changsong Zhou at the Centre for Nonlinear Studies, Hong Kong Baptist University, Hong Kong

Technical skills

Programming	Proficient in MATLAB, R, Python, and C#
Tools	EEGLAB, R Studio, Unity

Languages

English	Proficient
German	B1 Level
Hindi	Mother Tongue