HOW NEURAL DYNAMICS SHAPE THOUGHT DIMENSIONS

JINGYU HUA

Thesis submitted to the University of Ottawa
in partial Fulfillment of the requirements for the
PhD in Psychology

School of Psychology
Faculty of Social Sciences
University of Ottawa

Table of Contents

Preface

The experimental paradigms were designed by J Hua with inputs from G Northoff. The pilot study, the full experimental studies and all data analysis were completed by J Hua, with supervision and direction by G Northoff and S Fogel. Ideas for analysis and feedback on results was provided by G Northoff and S Fogel.

The manuscripts for articles were written by J Hua, with input on the introduction and discussion by G Northoff. S Fogel provided valuable feedback on manuscripts.

The study was approved by the Research Ethics Board of the Institute of Mental Health Research at the University of Ottawa (REB # 2016004). All work was done with their approval and according to their procedures.

All participants in the study provided written and verbal informed consent prior to study participation.

Acknowledgements

The completion of this doctoral dissertation has been a long and challenging journey, one that would not have been possible without the support, guidance, and encouragement of many individuals to whom I am deeply grateful.

First and foremost, I would like to express my heartfelt thanks to my two supervisors, Professor Georg Northoff and Professor Stuart Fogel. Professor Northoff has been a constant source of intellectual inspiration throughout my doctoral studies. His deep philosophical insight and theoretical vision have profoundly shaped the way I think about the brain and mind. Our frequent discussions about the core themes of this dissertation helped sharpen my ideas and expand my perspectives. He generously offered numerous valuable suggestions that pushed the boundaries of my thinking and guided me toward more rigorous and meaningful research. Professor Fogel, with his meticulous scientific approach and extensive expertise in EEG research and statistics, provided essential technical support and practical advice. I am especially grateful for his detailed and constructive feedback on the writing and revision of this dissertation, which greatly improved its structure, clarity, and overall quality. The complementary mentorship of both professors has been instrumental to my academic development and the successful completion of this thesis. Their trust and support have served as a solid foundation throughout this journey.

I also wish to express my deepest gratitude to my family. Your unwavering understanding, encouragement, and love have been my greatest source of strength during the most difficult times. Without your constant support behind the scenes, I would not have been able to devote myself so fully to my research and studies.

I am also sincerely thankful to the faculty members at Zhejiang University and Shenzhen University, who generously provided access to experimental equipment and laboratory space. Your support was crucial for the successful execution of my experiments and data collection, which laid the groundwork for this dissertation.

Finally, I want to thank all the colleagues, collaborators, and friends who have accompanied me on this journey. Every discussion, every piece of advice, and every word of encouragement has been a precious part of this process.

With this acknowledgment, I extend my deepest appreciation to all those who have supported me along the way.

Abbreviation Table

Abbreviation	**Full Term**
ADHD	Attention Deficit Hyperactivity Disorder
CEVS	Chinese Emotional Visual Stimulus
CPz	Central-Parietal Midline Electrode
DAN	Dorsal Attention Network
DMN	Default Mode Network
DTW	Dynamic Time Warping
EEG	Electroencephalography
ERP	Event-Related Potential
FIR	Finite Impulse Response
FP	Frequency Power
FS	Frequency Sliding
FT	Finger Tapping
Fz	Frontal Midline Electrode

GAM	General additive model
GLMM	Generalized Linear Mixed Model
Hz	Hertz
ICA	Independent Component Analysis
IPI	Inter-Probe Interval
ITI	Inter-Trial/Tapping Interval
ITPC	Inter-Trial Phase Coherence
ITPCz	Z-transformed Inter-Trial Phase Coherence
JE	Joint Entropy
LMM	Linear Mixed Model
MEG	Magnetoencephalography
PANAS	Positive and Negative Affective Schedule
PCA	Principal Component Analysis
PE	Precision Error
RT	Reaction Time

RTT	Reaction Time Task
SART	Sustained Attention to Response Task
SD	Standard Deviation
SE	Sample Entropy
SEM	Standard Error of the Mean
SI	Standard Interval
STTT	Spatio-Temporal Theory of Thought
TMS	Transcranial Magnetic Stimulation
TTV	Trial-to-Trial Variability
VAN	Ventral Attention Network
VAS	Visual Analogue Scale
fMRI	Functional Magnetic Resonance Imaging

Glossary

Term	**Definition**
Spontaneous Thought	A mental state or sequence of states that arises without external stimuli or deliberate effort.
Mind-Wandering	The phenomenon where attention drifts away from the current task towards unrelated thoughts.
Task-Relatedness	The extent to which a thought is relevant to the current task (on-task vs. off-task).
Thought Content Quantity	The number of different thoughts occurring simultaneously (single vs. multiple).
Thought Orientation	Whether thoughts are directed internally (self-focused) or externally (environment-focused).
Deliberate Control	The extent to which thoughts are voluntarily controlled (deliberate vs. spontaneous).
Goal-Directed Hypothesis	A theory suggesting that spontaneous thought results from a failure of executive control to focus on the task.
Perceptual Decoupling Hypothesis	The idea that mind-wandering occurs when sensory perception is disengaged from external stimuli, leading to internally-oriented thought.
Deliberate Constraint Hypothesis	A framework suggesting that thought varies in the level of constraint, ranging from deliberate to spontaneous.
Neural Dynamic	The evolving patterns of activity in neural oscillation over time.

Peak Frequency Sliding (FS)	the first derivative of the phase time series, indicating neural speed.
Sample Entropy (SE)	A measure of unpredictability and flexibility in neural oscillations.
Inter-Trial Phase Coherence (ITPC)	A measure of the consistency of neural oscillatory phases across trials.
Topographic Similarity	A measure of the spatial stability of EEG signals over time, indicating neural timescales.
Neural Entropy	A measure of randomness or variability in neural activity, associated with cognitive complexity.
Reaction Time (RT)	The time taken to respond to a stimulus.

Abstract

Background

Spontaneous thought, particularly exemplified by mind-wandering, is characterized by a complex and multidimensional structure. This structure spans several dimensions: (1) task-relatedness (on-task vs. off-task), (2) thought content quantity (single vs. multiple), (3) thought orientation (externally vs. internally oriented), and (4) deliberate control (deliberate vs. spontaneous). While previous research has investigated these dimensions individually, a comprehensive neurodynamic framework integrating their cognitive and neural mechanisms remains lacking.

Aims and Hypotheses

This thesis aims to examine the neural underpinnings of spontaneous thought through cognitive testing and electroencephalography (EEG), identifying distinct neural markers for each dimension and exploring their interrelationships. It is hypothesized that:

1. Alpha and theta oscillations will track task-relatedness and thought content quantity,
2. Task-relatedness and thought orientation will be distinguishable through neural and behavioral timescales, with task-relatedness operating on a shorter timescale than thought orientation.
3. Task-relatedness and deliberate control are tightly linked, with on-task thoughts typically being deliberate and off-task thoughts being spontaneous. Pre-stimulus neural oscillatory phase measures will predict post-stimulus task-related behaviors.

Methods

Three EEG studies were conducted to examine these hypotheses. Study 1 analyzed the relationship between task-relatedness and thought content quantity using EEG measures of alpha and theta peak frequency sliding. Study 2 investigated task-relatedness and thought orientation by comparing their neural and behavioral timescales. Study 3 explored the interaction between task-relatedness and deliberate control, using phase-based neural markers such as peak frequency sliding, sample entropy, and inter-trial phase coherence.

Results

Study 1 revealed that alpha and theta FS tracked task-relatedness and thought content quantity, with increased alpha FS associated with on-task, single-content thoughts and increased theta FS with off-task, multiple-content thoughts. Study 2 found that task-relatedness operates on a shorter timescale than thought orientation at both neural and behavioral levels. Study 3 demonstrated a strong link between task-relatedness and deliberate control, where on-task thoughts were typically deliberate and off-task thoughts were spontaneous. Furthermore, pre-stimulus neural oscillatory phase measures predicted post-stimulus task-related behaviors.

Conclusion

These findings provide empirical support for the multidimensional nature of spontaneous thought and highlight distinct neural markers for each dimension. By integrating cognitive and neurophysiological evidence, this thesis establishes a neurodynamic framework for spontaneous thought, offering novel insights into the study of thought.

General Introduction

Context: The Multidimensional Nature of Thought and its Neural Dynamics

Despite its ubiquity, *thought*—and spontaneous thought in particular—has proven notoriously difficult to define in a precise and unified manner. As argued by Seli and colleagues (2018), phenomena such as mind-wandering resist classical definitions with necessary and sufficient conditions, because they encompass a heterogeneous set of experiences that vary along multiple partially overlapping dimensions. Precisely because of this multidimensional and graded nature, neuroscientific research on spontaneous thought—especially mind-wandering—has often focused on isolating specific dimensions, while neglecting the broader multidimensional structure of such cognition(Barron et al., 2011; Christoff, 2012; Christoff et al., 2016; Smallwood & Schooler, 2006). This limitation has led to fragmented theories, lacking an integrated neurodynamic framework that captures the full complexity of thought processes. The central issue addressed in this thesis is how these dimensions can be distinguished and integrated at the neural level, and whether neural dynamics provide a unifying principle for understanding the structure of thought.

Spontaneous thought varies across multiple dimensions, including task-relatedness (Barron et al., 2011; Groot et al., 2022; Irving, 2016; Seli, Kane, Metzinger, et al., 2018; Smallwood & Schooler, 2006), thought content quantity (Alperin et al., 2021; Christoff et al., 2016, 2018; Mills et al., 2018, 2021), orientation (Bocharov et al., 2019; Kucyi et al., 2021; Rostami et al., 2022; Vanhaudenhuyse et al., 2011), and deliberate control (Christoff et al., 2016, 2018). Each of these dimensions reflects distinct cognitive mechanisms, yet their neural underpinnings and interrelationships remain poorly understood. Neural oscillatory dynamics, including phase dynamics (Cohen, 2014a), neural timescales (Golesorkhi, Gomez-Pilar, Tumati, et al., 2021; Golesorkhi, Gomez-Pilar, Zilio, et al., 2021; Murray et al., 2014; Raut et al., 2020; Wolff et al., 2022), and entropy (Bravi et al., 2011), are defining characteristics of thought processes. However, how these neural features differentially contribute to various thought dimensions remains an open question.

Literature review

Different thought dimensions

Spontaneous thought (e.g., mind wandering) has received increasing attention in recent years (Andrews-Hanna et al., 2018; Baird et al., 2014; Christoff et al., 2016; Marchetti et al., 2016;

Schooler et al., 2011; Seli, Kane, Metzinger, et al., 2018; Seli, Kane, Smallwood, et al., 2018; Smallwood & Schooler, 2006). Spontaneous thought is defined as a mental state, or sequence of states, that arise without external stimuli or deliberate intent/effort (Chen et al., 2014; Christoff et al., 2016; Smallwood, 2013). Several influential hypotheses have attempted to explain spontaneous thought, each focusing on a specific feature, or dimension:

The '***goal directed hypothesis***' suggests that spontaneous thought, such as mind wandering, is a failure of executive control to focus on and perform the task at hand (Barron et al., 2011; Groot et al., 2022; Smallwood & Schooler, 2006). This perspective emphasizes '***task-relatedness***', which assesses whether attention can be sustained on a current task, or not (**e.g., on-task vs. off-task thought**) (Barron et al., 2011; Groot et al., 2022; Irving, 2016; Seli, Kane, Metzinger, et al., 2018; Smallwood & Schooler, 2006).

The '***perceptual decoupling hypothesis***' describes spontaneous thought as being either internally oriented, or focused on the external environment (Bocharov et al., 2019; Kucyi et al., 2021; Schooler et al., 2011; Smallwood & Schooler, 2006; Stawarczyk et al., 2013). Thus, the perceptual decoupling theory focusses on '***thought orientation***'. This model posits that the extent of perceptual coupling determines whether cognition is primarily influenced by internal or external stimuli. (**e.g., externally vs. internally oriented thought**) (Bocharov et al., 2019; Kucyi et al., 2021; Rostami et al., 2022; Vanhaudenhuyse et al., 2011).

Finally, the '***deliberate constraint hypothesis***' emphasizes the dynamic nature of spontaneous thought, in terms of whether it is free or constrained (Christoff et al., 2016, 2018). The dimension of deliberate constraint differentiates between thoughts that are under deliberate control and those that occur freely (**e.g., deliberate vs. spontaneous thought**). This framework is unique in terms of defining spontaneous thought based on its *dynamic properties*. Spontaneous thoughts can also be characterized as ***'freely moving' thought*** (Alperin et al., 2021; Christoff et al., 2016, 2018; Mills et al., 2018, 2021). This may suggest the existence of an additional thought dimension: thought content quantity (**e.g., single vs. multiple thoughts**). More specifically, when a thought moves more freely, it exhibits greater fluctuations in attention (Mills et al., 2021) and tends to shift among multiple contents (Christoff et al., 2016). This is evident in extreme cases, such as attention deficit hyperactivity disorder (ADHD). Individuals with ADHD often experience difficulty stabilizing attention, leading to highly free-flowing thoughts (Alperin et al., 2021; Amrani & Golumbic, 2020; Bodalski et al., 2018; Christoff et al., 2016; Smallwood, 2013). At the other end of this spectrum, thoughts that are more singular in nature, such as in deep, focussed concentration, obsessive thought, or rumination.

One major shortcoming in the current literature is that each of these perspectives focus only on a single dimension of spontaneous thought. Given that spontaneous thought is undoubtedly multidimensional, this lack of integration leaves us with a fragmented understanding of how to characterize and measure spontaneous thought. Thus, a framework that integrates these distinct dimensions may further elucidate the nature of spontaneous thought and remains to be established.

There is currently no unifying theory or empirical research that comprehensively explains how these different dimensions of spontaneous thought are either interrelated or are orthogonal from one another. That said, some recent advancements on this front have been made. For example, the '*family resemblance hypothesis*' proposes that mind-wandering be treating as a graded, heterogeneous construct that should be measured along multiple dimensions (Seli, Kane, Metzinger, et al., 2018; Seli, Kane, Smallwood, et al., 2018). From this perspective, describing and defining spontaneous thought along a single dimension should be avoided in order to better capture the multidimensional nature of spontaneous thought. However, at present, little is known about the inter-relationships among the different, relatively well-established dimensions of spontaneous thought (Christoff et al., 2018). Experimental evidence investigating the distinctions among different known dimensions of spontaneous thought, both at neural and psychological levels, is essential for progress to be made in terms of a more fulsome understanding of mind wandering.

Therefore, it is crucial to understand in what ways the different dimensions of spontaneous thought are inter-related, or distinct from one another. This question remains unresolved, and is the overarching objective of the proposed research. In this study, we will examine various thought dimensions, including: **1)** task-relatedness (on vs. off task), **2)** orientation (internally vs. externally focused), **3)** deliberate constraint (deliberate vs. spontaneous), and, **4)** thought content quantity (single-multiple). We aim to propose how these dimensions are differentiated, and also interrelated from a cognitive and neurodynamic perspective.

Task relatedness (on vs. off-task thoughts)

Task-relatedness, commonly measured by comparing brain activity on- and off-task (**Figure A**), is a longstanding topic of investigation into the nature of thought. It plays a particularly prominent role in research on attention and mind-wandering (Alperin et al., 2021; Andrillon et al., 2021; Christoff et al., 2018; Irving, 2016; Smallwood & Schooler, 2006). The '*goal directed hypothesis*' considers spontaneous thought as a failure to maintain attention on the task-at-hand, i.e., "off-task thought" (Barron et al., 2011; Groot et al., 2022; Irving, 2016; Seli, Kane, Metzinger, et al., 2018; Smallwood & Schooler, 2006). At the neural level, off-task thought is primarily associated with increased activity within the default mode network (DMN). In contrast, on-task thought engages a broad array of cortical systems implicated in goal-directed behavior, most notably the frontoparietal control network (FPCN) as well as the dorsal and ventral attention networks (DAN and VAN) (Christoff et al., 2009; Fox et al., 2015; Groot et al., 2022; Turnbull, Wang, Murphy, et al., 2019).

Thought content quantity (single vs. multiple thoughts)

However, distinguishing between on- *vs*. off-task thought does not necessarily provide any insight into the contents of thought, *per se*. On-task thoughts are generally assumed to be "single thought", as opposed to multiple, divergent streams of thought, given the need to focus on a particular stimulus or task (Alperin et al., 2021; Christoff et al., 2018; Mills et al., 2018, 2021). On-task thoughts are constrained and directed toward the task at hand, usually involving a single content focus. However, the precise nature of off-task thoughts remains less clear: are they singular or varied in content? Although this question remains relatively underexplored, existing evidence indicates that off-task thoughts—such as mind-wandering—are typically characterized by internally generated thought content. These thoughts often arise spontaneously and are minimally guided or constrained. (Alperin et al., 2021; Christoff et al., 2016; Mills et al., 2018). This freedom allows off-task thoughts to switch more readily among multiple contents. In Study 1, we adopt the premise that on-task thoughts are typically limited to a single, focused content. In contrast, off-task thoughts are generally less constrained and involve multiple, variable contents.

Thought orientation (internal vs. external thoughts)

The "*Perceptual Decoupling Hypothesis*" (Kam & Handy, 2013; Schooler et al., 2011; Smallwood, 2013; Smallwood & Schooler, 2006) suggests that off-task thoughts, such as mind-wandering, occur due to a decoupling of sensory and motor functions from environmental input and output. This decoupling shifts perception and action from externally- to internally-oriented thought. Evidence for this includes disruptions in phase locking of the EEG between ongoing neural oscillations and external perceptual inputs that occur during spontaneous thought (Baird et al., 2014; Brandmeyer & Delorme, 2020). Furthermore, during spontaneous thought, brain activity shifts from sensory cortex areas, which support perception, toward the default mode network (DMN), which facilitates internal thought (Geden et al., 2018; Smallwood et al., 2013). These findings suggest that perception becomes decoupled from the external environment, and the mind reorients toward internal thought during spontaneous thought.

By contrast, externally-oriented thoughts correlate with recruitment of the dorsolateral prefrontal cortex and inferior parietal lobule, brain areas involved in goal-directed thought (Boly et al., 2007; Watanabe, 2017) and input from the external environment (Alpert et al., 2008; Kajimura & Nomura, 2015). Several studies have subsequently confirmed the reciprocal relationship between DMN and unimodal sensory regions, providing a wealth of knowledge in terms of the neural basis of internally- and externally-oriented thought (see also Dixon et al., 2014 for a review and framework of internally- vs. externally-oriented cognition as well as Ho et al., 2020; Konu et al., 2020; Murphy, Poerio, et al., 2019; Murphy, Wang, et al., 2019; Sormaz et al., 2018; Turnbull, Wang, Murphy, et al., 2019; Turnbull, Wang, Schooler, et al., 2019). This body of literature emphasizes the central role of the default mode network (DMN) in generating internally oriented thought. The DMN operates on a longer timescale compared to goal-directed brain regions, such as the dorsal and ventral attention networks (DAN and VAN), which are associated with on- and off-task processing. Based on these findings, thought orientation (internal vs. external) will exhibit slower dynamics than task-relatedness (on vs. off task), at both the behavioral and neural level. This will be explored in **Study 2**.

Deliberate control (spontaneous vs. deliberate thoughts)

Christoff et al. proposed the '*deliberate constraint hypothesis*', a dynamic perspective that considers the level of constraint on thought content as the main feature distinguishing different types of thoughts. They further categorized constraints into two dimensions: automatic and deliberate constraints (Christoff et al., 2016, 2018). In this framework, spontaneous thoughts are described as unguided, wandering thoughts, which include thoughts during dreaming and those related to creativity (Christoff et al., 2016; Girn et al., 2020; Seli, Kane, Smallwood, et al., 2018). These thoughts are less cognitively constrained and appear highly dynamic, as they are 'free-moving and task-unrelated' (Alperin et al., 2021; Christoff et al., 2016; Girn et al., 2017; Mills et al., 2018). Spontaneous thoughts are maximally free-flowing in a dynamic manner, as seen in states like creativity (Dolan et al., 2018), psychedelic states (Girn et al., 2020), and dreams (Christoff et al., 2016).

Task-relatedness is often presumed to be synonymous with deliberate control, as off-task thoughts are typically spontaneous in nature, while on-task thoughts are generally governed by cognitive control (Christoff et al., 2016, 2018; Mills et al., 2021). However, these dimensions are not entirely overlapping (Mills et al., 2018). For instance, creative thinking represents a form of thought that exhibits relatively low deliberate constraint while remaining highly task-related (on-task thought) (Christoff et al., 2016). Are these dimensions dissociated with each other? Furthermore, what role does deliberate control play in contributing to the current task? These unresolved questions will be addressed in **Study 3**.

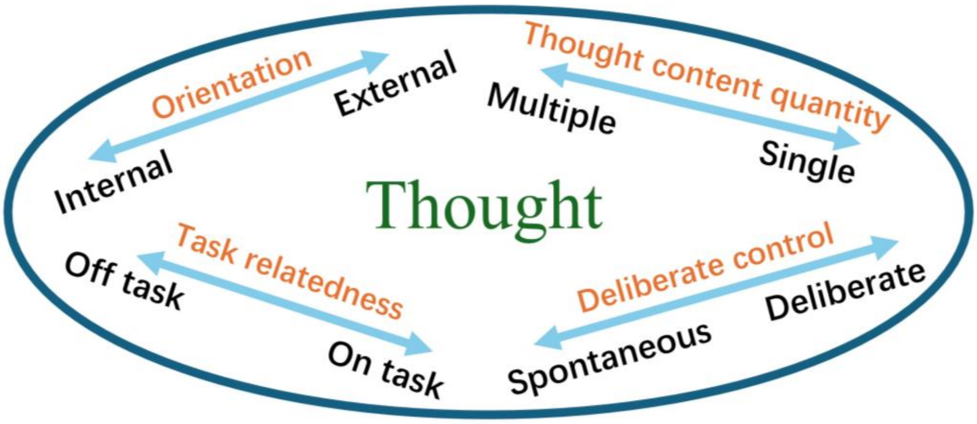


Figure A. Dimensions of thought. In this study, thought will be divided into four dimensions: **1) Orientation:** Thoughts can range from being internally oriented) to externally oriented; **2) Task Relatedness**: Thoughts may vary in their relation to a specific task, ranging from off-task to on-task; **3) Deliberate Control**: Thoughts can be classified based on the level of control involved, spanning from spontaneous to deliberate; **4) Thought Content Quantity**: This dimension captures the multiplicity of thoughts, ranging from multiple to single.

The Neural dynamics underlying thoughts

Neural Dynamics refers to the evolving patterns of activity in neural oscillation over time (Kolvoort et al., 2020; Langdon & Chaudhuri, 2021; Northoff, Buccellato, et al., 2024; Northoff et al., 2020a). Emerging evidence suggests that neural dynamical properties play a crucial role in shaping human cognition and thought processes (Kolvoort et al., 2020; Northoff, Buccellato, et al., 2024; Northoff et al., 2020a). In this study, we focus specifically on three key neural dynamical features and explore their underlying mechanisms in thought.

Phase dynamics

Neural oscillations, such as those measured by EEG originate from rhythmic activity that reflects fluctuations in the excitability of large populations of neurons. Oscillations are characterized by three key parameters: frequency, power, and phase (**Figure B**). Frequency, measured in hertz (Hz), represents the speed of oscillation, indicating the number of cycles per second. Power represents the energy within a frequency band and typically is calculated as the squared amplitude of the oscillation. Phase indicates the position along the sine wave at a specific point in time and is measured in radians or degrees. Importantly, power and phase operate independently, meaning that neural dynamics captured by power are distinct from those represented by phase (Cohen, 2014a).

In this thesis, we focus particularly on phase dynamics rather than power fluctuations for two key reasons: **1)** Spontaneous thought is an ongoing process influenced by inputs from both internal sources (e.g., memory) and external sources (e.g., the environment) (Andrews-Hanna et al., 2018; Babo-Rebelo et al., 2016; Smallwood & Schooler, 2006). The phase of neural oscillations has been shown to play a critical role in the encoding of these neural inputs (Catalano et al., 2024; Cohen, 2014b), which is essential for supporting thought processes; **2)** Power measurements, such as ERP components, may be the result of phase resetting (Hanslmayr et al., 2006). This implies that observed ERP power changes after averaging could originate from phase dynamics (e.g., due to phase alignment) rather than power fluctuations alone.

Figure B. Adapted from *Analyzing Neural Time Series Data Theory and Practice* (Cohen, 2014a), illustrating the three dimensions that define neural oscillations.

Phase dynamics can be assessed by measuring the speed of neural oscillations, specifically through peak frequency sliding. Frequency sliding is derived by applying a Hilbert transform to the band-pass–filtered signal to extract the instantaneous phase, followed by computing the first derivative of the phase time series (details of the calculation can be found in supplementary materials). This procedure provides a moment-to-moment estimate of the speed of phase shift, thereby indexing the instantaneous frequency of the oscillation. Higher frequency sliding values correspond to faster oscillatory dynamics, whereas lower values indicate slower oscillatory activity(Cohen, 2014b).. Phase dynamics can also be assessed by measuring the peak frequency. Computational models and EEG studies have shown that alpha frequency sliding increases with greater neural input (Cohen, 2014b; Mierau et al., 2017). For example, alpha frequency sliding can reflect the strength of visual input (Cohen, 2014b). Thus, suggesting that higher cognitive loads during external tasks are associated with increased alpha frequency sliding. Accordingly, alpha frequency sliding is an ideal candidate for tracking the cognitive load and dynamics of on-task thoughts (Cohen, 2014b; Wolff, de la Salle, et al., 2019).

Unlike the extensively studied alpha frequency sliding, theta frequency sliding has received less attention. Recent studies have linked theta frequency sliding to on-off task thought, though not directly. For instance, findings suggest that increased theta frequency sliding (accompanied by decreased alpha frequency sliding) is related the disruption of thoughts on the task-at-hand, caused by rumination in major depressive disorder (Wolff, de la Salle, et al., 2019). In addition, in a study where theta frequency sliding was manipulated using TMS, it was observed that reduced theta frequency sliding enhanced working memory related to the current task (Wolinski et al., 2018). Moreover, theta frequency sliding is believed to have a specific relationship with alpha frequency sliding, where their harmonics work together to facilitate the processing of high cognitive loads (Rodriguez-Larios & Alaerts, 2019). These findings suggest that phase dynamics in the alpha and theta bands, as measured by alpha and theta frequency sliding, underlie dimensions of thought such as the task-relatedness (**Figure C**).

Neural timescales

The dynamic range of spontaneous thought spans timescale intervals that are orders of magnitude apart: from minutes, to seconds, to milliseconds. Functional connectivity as measured by fMRI, is related to fluctuations in the infra-slow frequency range (0.01 to 0.1Hz) with a timescale of 100s to 10s. By comparison, EEG and MEG operate in the much faster frequency range, ranging from 1Hz to 100Hz, with timescales ranging from1ms to 1s (Buzsaki, 2006). Multiple modalities—including EEG, MEG, fMRI, and intracranial recordings—provide converging evidence that thought dynamics unfold across a wide range of frequency bands (Smallwood, Bernhardt, et al., 2021; Smallwood, Turnbull, et al., 2021). These dynamics span infra-slow (0.01–0.1 Hz), slow (0.1–1 Hz), and fast (1–100 Hz) frequencies, corresponding to timescales from hundreds of seconds to milliseconds..

The vastly different timescales (e.g., infra-slow, slow and fast) suggests that our thoughts may be captured by multi-scale temporal dynamics. Studies have revealed a temporal hierarchy in intrinsic neural timescales. In both infra-slow (0.01–0.1 Hz) and faster (1–40 Hz) frequency ranges, timescales are longer in regions such as the default mode network (DMN) and shorter in sensory areas (Golesorkhi, Gomez-Pilar, Tumati, et al., 2021; Golesorkhi, Gomez-Pilar, Zilio, et al., 2021; Murray et al., 2014; Raut et al., 2020; Wolff et al., 2022). These temporal layers align with spatial gradients along the DMN–sensory axis (Golesorkhi, Gomez-Pilar, Tumati, et al., 2021). Trans-modal regions such as the DMN exhibit longer timescales, whereas unimodal sensory regions exhibit shorter timescales (Kiebel et al., 2008; Margulies et al., 2016; Taylor et al., 2015; Wolff et al., 2022). Such a gradient of timescales across brain regions may support the variability of timescales among different types of thoughts. Internal and off-task thoughts are associated with the activation of DMN (Christoff et al., 2016; Kucyi, 2018; Kucyi et al., 2018, 2021; Smallwood, Bernhardt, et al., 2021), which operate on longer timescales (Golesorkhi, Gomez-Pilar, Tumati, et al., 2021; Golesorkhi, Gomez-Pilar, Zilio, et al., 2021; Murray et al., 2014; Raut et al., 2020; Wolff et al., 2022). By contrast, external and on-task thoughts are linked to the activation of sensory regions (Baird et al., 2014; Schooler et al., 2011), which function on shorter timescales (Golesorkhi, Gomez-Pilar, Tumati, et al., 2021; Golesorkhi, Gomez-Pilar, Zilio, et al., 2021; Murray et al., 2014; Raut et al., 2020; Wolff et al., 2022).

As mentioned above, different brain regions operate on distinct timescales, and these varying large-scale networks serve as the foundation of thought (Bressler & Menon, 2010; Christoff et al., 2016; Kucyi et al., 2017, 2018; Seli, Kane, Smallwood, et al., 2018). Therefore, when analyzing timescales, it is essential to employ a method that also captures topography rather than relying on a single regions/sites/electrode. This can be measured using ‘topographic similarity,’ which quantifies the resemblance between the topographic distribution at a given time point and those at subsequent time points (Luo et al., 2024; Tian & Huber, 2008). More specifically, topographic similarity measures the extent to which the spatial configuration of EEG signals at earlier time points influences their spatial distribution at a later time point (Luo et al., 2024; Tian & Huber, 2008). A higher degree of topographic similarity indicates a stronger influence of past configurations on the present, reflecting a greater temporal integration of past and present inputs over a specific time period (Wolff et al., 2022; Wolman et al., 2023). Thus, topographic similarity serves as a neural marker for the duration of neural activity and provides a measure of the timescale associated with an underlying neural process. This approach allows for a more comprehensive analysis of neural timescales, highlighting the dynamic interplay between past and present neural states in shaping cognitive processes.

Neural entropy

Entropy represents the uncertainty of neural oscillations by quantifying the probability changes from one time point to the next (Aboy et al., 2007; Gosseries et al., 2011; Lau et al., 2022). Oscillations with low predictability are characterized by high entropy, while highly ordered and predictable signals (e.g., sine waves with a fixed frequency) exhibit very low entropy (Aboy et al., 2007; Gosseries et al., 2011; Lau et al., 2022). This uncertainty can be measured through entropy, which can be assessed using various methods in either the time domain or frequency domain (Bravi et al., 2011). A common approach is to measure entropy in the time domain using Sample entropy, which describes the unpredictability in a time series from point to point.

The entropy of the brain's spontaneous activity decreases when awareness is reduced (Barttfelda et al., 2015; Bodart et al., 2017; Casali et al., 2013; Chennu et al., 2014; D'Andola et al., 2018; Gosseries et al., 2011; Hudetz et al., 2015; Sarasso et al., 2015; Sitt et al., 2014; Tagliazucchi & Laufs, 2014). This pattern indicates a direct relationship between entropy at the neural level, and the awareness at the psychological level. As awareness is tightly linked with deliberate control, i.e., less awareness is related with lower level of deliberate control (Christoff et al., 2018; Mierau et al., 2017), the reduction in neural entropy is suggested to be associated with decrease of deliberate control.

Taken together, these findings suggest that reductions in neural entropy are directly linked to a decline in the deliberate control of thought. As entropy diminishes, the brain's spontaneous activity becomes more predictable and less varied. This implies that lower levels of neural entropy correspond to less deliberate control at the psychological level. Future studies are warranted to investigate entropy not only at the neural level but also in a more direct manner at the psychological level, for instance, how entropy links thought (deliberate control) and task-related responses.

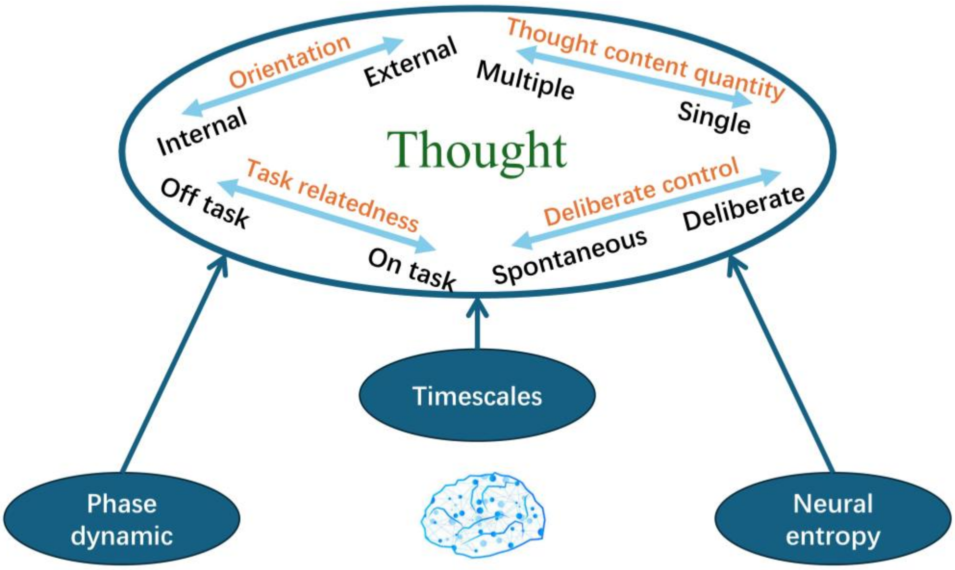


Figure C. Resume of the present thesis. In this thesis, we plan to explore the neural basis of thought dimensions on three neural aspects: **1) Phase Dynamic**: Phase dynamic, measured by the peak frequency of neural oscillations, reflects how neural activity changes in response to cognitive load and information input; **2) timescales:** Neural timescales which can be measured by topographic similarity represent the different temporal layers of brain activity, reflecting a hierarchical organization of thought processes. and 3) **Neural Entropy**: Neural entropy quantifies the variability or unpredictability of neural signals. Higher entropy is associated with greater cognitive flexibility, awareness, and deliberate control, particularly under increased cognitive demands.

The broad aim of this doctoral thesis is to investigate the neurodynamic mechanisms underlying the multidimensional nature of spontaneous thought. This research is conducted at three levels:

(1) by examining how task-relatedness and thought content quantity are tracked by alpha and theta peak frequency sliding (FS);

(2) by investigating how task-relatedness and thought orientation are dissociated through neural and behavioral timescales;

(3) by exploring the interaction between task-relatedness and deliberate control and how neural oscillatory phase measures (e.g., FS, sample entropy (SE), and inter-trial phase coherence (ITPC)) link pre-stimulus spontaneous thought with post-stimulus task-related behaviors.

By integrating findings from these studies, this thesis aims to establish an empirical and theoretical foundation for a neurodynamic model of spontaneous thought.

Study 1 Summary

Background

Spontaneous thought is highly dynamic, continuously fluctuating in content and structure. One key distinction in thought processes is **task-relatedness**—whether a thought is focused on an external task (on-task thought) or detached from it (off-task thought). Traditional theories, such as the Perceptual Decoupling Hypothesis, suggest that off-task thoughts occur due to a decoupling of sensory perception from external stimuli (Barron et al., 2011; Groot et al., 2022; Irving, 2016; Seli, Kane, Metzinger, et al., 2018; Smallwood & Schooler, 2006). However, existing studies have largely overlooked the quantity of thought contents held simultaneously.

While on-task thoughts are generally focused on a single content, off-task thoughts tend to be multiple-content, involving simultaneous, non-sequential mental representations (Mills et al., 2018) . This distinction suggests that on- and off-task thoughts not only differ in content relevance but also in their cognitive load and dynamic complexity.

Neuroscientific research indicates that different frequencies are associated with different cognitive states. The alpha frequency band (8-13 Hz) is linked to externally directed, task-related cognition, while the theta frequency band (5-8 Hz) is associated with internally generated, unconstrained thought (Arnau et al., 2020; Baldwin et al., 2017; Jin et al., 2019). However, previous research has primarily focused on power changes in these frequencies, neglecting more dynamic measures such as FS — a phase-based measure of neural oscillatory speed that can capture rapid shifts in thought (Cohen, 2014a, 2014b; Grandy et al., 2013).

This study aims to investigate whether alpha and theta FS can track the dynamic shifts in thought along two dimensions: 1) task relatedness: on-task vs. off-task thoughts, and, 2) thought content quantity: single vs. multiple content thoughts. Furthermore, the study seeks to determine whether alpha and theta oscillatory dynamics serve as a neural marker of thought content quantity, with alpha tracking single-content thoughts and theta tracking multiple-content thoughts.

Aim

This study aims to investigate the neurodynamic mechanisms underlying the multidimensional nature of spontaneous thought by addressing two key objectives:

1. The interaction between task-relatedness and thought content quantity—to examine whether these two dimensions (1. task relatedness: on-task vs. off-task, and, 2. Thought content quantity: single vs. multiple contents) are independent or interdependent at the behavioral and neural levels.
2. The role of alpha and theta oscillations in tracking thought dynamics—to determine whether alpha and theta FS serves as a neural marker distinguishing different thought states.

Hypothesis

1. Task-relatedness and thought content quantity will be inter-related: on-task thoughts will be predominantly single-content, and off-task thoughts will be more likely to involve multiple contents. This interaction will also be reflected at the neural level.
2. Alpha FS will be higher during on-task, single-content thoughts while theta FS will be higher during off-task, multiple-content thoughts. The relative changes in alpha and theta FS will provide a more reliable marker of thought dynamics than traditional power measures, suggesting that phase-based oscillatory processes play a key role in tracking different cognitive states.

This study aims to provide a unified neurodynamic model that captures the complex interaction between task-relatedness and thought content quantity, shedding light on the oscillatory mechanisms underlying spontaneous thought.

Study 2 Summary

Background

Human thoughts are multidimensional and can be classified along distinct dimensions such as task-relatedness (on-task vs. off-task) (Hua et al., 2022; Kam et al., 2022; Smallwood & Schooler, 2006; Stawarczyk et al., 2020) and thought orientation (external vs. internal) (Kucyi et al., 2018; Rostami et al., 2022; Vanhaudenhuyse et al., 2011). While task-relatedness refers to whether thoughts are focused on an ongoing task, thought orientation concerns whether thoughts are directed toward the external environment or internally towards the self. Traditionally, these two dimensions were considered equivalent, with on-task thought assumed to be externally oriented and off-task thought presumed to be internally oriented (Andrews-Hanna et al., 2010; Arnau et al., 2020; Bastian & Sackur, 2013). However, recent studies challenge this assumption, suggesting that task-relatedness and thought orientation are distinct dimensions of thought with different neural correlates and temporal dynamics (Barron et al., 2011; Christoff et al., 2016; Smallwood & Schooler, 2006).

One key unresolved question is whether these two dimensions can be differentiated in terms of their temporal characteristics, i.e., their timescales or durations, at both the behavioral and neural levels. Previous research suggests that thoughts related to task performance involve shorter timescales with rapid updates of neural activity, whereas internally-oriented thoughts involve longer timescales, integrating information over extended timeframes (Rostami et al., 2022; Vanhaudenhuyse et al., 2011). However, the extent to which task-relatedness and thought orientation are distinguished by different temporal properties at both behavioral and neural levels remains unclear.

In addition, recent findings suggest that the relationship between thought content and its behavioral or neural correlates may be nonlinear (Huang et al., 2017; Wolff, Yao, et al., 2019). Such nonlinearities may obscure standard linear effects and require more flexible models to capture underlying dynamics (Huang et al., 2017; Northoff, Buccellato, et al., 2024; Wainio-theberge et al., 2020). Moreover, traditional power-based EEG metrics may fail to detect relevant neural signatures, as phase-based neural coherence—such as phase-locking value (PLV)—may better reflect the large-scale temporal coupling of brain regions involved in spontaneous thought (Fries, 2005; Knyazev et al., 2011).

To address these gaps, this study investigated the timescales of task-relatedness and thought orientation using behavioral measures (finger tapping) and neural measures (EEG-based topographic similarity). By dissociating the two thought dimensions based on their timescales and modeling their associations beyond linear effects, the study aims to provide novel insights into the temporal structure of thought processes.

Aim

This study aims to investigate whether task-relatedness (on vs. off-task) and thought orientation (internal vs. external) can be distinguished by their temporal dynamics at both the behavioral and neural levels. Specifically, the study has four key objectives:

1. To examine how task-relatedness and thought orientation interact at different behavioral timescales, using fast vs. slow finger tapping as a proxy for short vs. long timescales.
2. To investigate whether task-relatedness and thought orientation are associated with different neural timescales, using EEG-based topographic similarity to measure the duration of neural activity integration.
3. To explore whether the associations between thought dimensions and behavioral as well as neural timescales are mediated by nonlinear relationships, using generalized additive models (GAMs) and Bayesian mediation analysis.
4. To assess whether phase coherence (as measured by PLV), rather than power-based neural activity, underlies the neural representation of temporal dynamics in thought.

This study examines thought processes at both behavioral and neural levels. It aims to determine whether distinct thought dimensions are associated with specific temporal properties and mechanistic pathways. In particular, it tests the hypothesis that task-relatedness is linked to shorter timescales, whereas thought orientation corresponds to longer timescales.

Hypothesis

1. At the behavioral level, task-relatedness (on vs. off-task) will be associated with shorter timescales, as reflected in precision error (PE) during fast finger tapping. Thought orientation (internal vs. external) will be associated with longer timescales, as reflected in PE during slow finger tapping.
2. At the neural level, task-relatedness will correlate with shorter neural timescales, reflected in topographic similarity over shorter durations during fast finger tapping. Thought orientation will correlate with longer neural timescales, reflected in topographic similarity over longer durations during slow finger tapping.
3. At the modeling level, the relationship between thought dimensions and both PE and topographic similarity will be nonlinear.
4. At the mechanistic level, topographic similarity will be driven by phase coherence rather than power, indicating that phase dynamics mediate the influence of thought on neural activity.

This study seeks to establish that task-relatedness and thought orientation are distinct dimensions of thought that operate on different temporal scales, and rely on distinct neurodynamic mechanisms, both at the behavioral and neural levels.

Study 3 Summary

Background

Ongoing thoughts fluctuate, influencing cognition and behavior (Christoff et al., 2016; Girn et al., 2020; Hua et al., 2022; Kucyi, 2018; Rostami et al., 2022; Scalabrini et al., 2022; Smallwood, Bernhardt, et al., 2021; Smallwood, Turnbull, et al., 2021; Vanhaudenhuyse et al., 2011). Mind-wandering, for example, negatively affects task performance by increasing reaction times (RT) and reducing accuracy (Alperin et al., 2021; Barron et al., 2011; Christoff et al., 2016; Girn et al., 2020; Smallwood & Schooler, 2006). However, the neural mechanisms that connect different thought dimensions to task-related performance remain unclear. Prior research has identified two key dimensions of thought: task relatedness (on-task vs. off-task) and deliberate control (deliberate vs. spontaneous thoughts) (Barron et al., 2011; Christoff et al., 2016, 2018; Smallwood & Schooler, 2006). Traditional views such as the '*goal directed hypothesis*' assume that these dimensions overlap, with off-task thoughts being more spontaneous and on-task thoughts being more deliberate (Barron et al., 2011; Groot et al., 2022; Irving, 2016; Seli, Kane, Metzinger, et al., 2018; Smallwood & Schooler, 2006). However, emerging evidence suggests that they are distinct, as deliberate thoughts can be off-task, and spontaneous thoughts can still be task-related (Mills et al., 2018).

To clarify how these thought dimensions impact cognition and behavior, this study examines the relationship between thought dimension, pre-stimulus neural oscillations, post-stimulus neural coherence, and behavioral responses. Specifically, the study investigates how ongoing thought influences RT by affecting pre-stimulus neural dynamics such as FS and SE, which in turn affect post-stimulus ITPC.

Aim

This study aims to establish a mechanistic link between ongoing thought dimensions, neural dynamics, and task-related behavior. The specific objectives are:

1. **Investigate the relationship between thought dimensions and pre-stimulus neural dynamics:** Examine how on-task vs. off-task thoughts and deliberate vs. spontaneous thoughts affect two key neural measures: **FS:** A measure of neural speed, where higher FS indicates faster oscillations; **SE**: A measure of neural unpredictability or flexibility, with higher SE reflecting greater adaptability.
2. **Examine how pre-stimulus neural activity influences post-stimulus neural phase coherence:** 1) Assess whether changes in FS and SE impact ITPC, a measure of how consistently neural oscillations align across trials; 2) determine whether increased FS and SE before stimulus onset enhance ITPC in the post-stimulus period.

3. Determine how post-stimulus neural phase coherence affects RT: Test whether 1) higher ITPC leads to faster RTs, providing a neural mechanism for how thought states influence behavior; 2) Investigate whether the relationship between pre-stimulus neural dynamics (FS, SE) and RT is mediated by post-stimulus ITPC.

Hypothesis

1. **Pre-stimulus neural dynamics hypothesis:** 1) On-task and deliberate thoughts will be associated with increased FS (faster oscillations) and higher SE (greater neural flexibility); 2) Off-task and spontaneous thoughts will be associated with lower FS (slower oscillations) and reduced SE (less neural flexibility).
2. **Pre-stimulus to post-stimulus neural continuity hypothesis:** Higher pre-stimulus FS and SE will lead to increased post-stimulus ITPC, indicating better neural synchronization across trials.
3. **Neural mediation of behavior hypothesis:** 1) Higher post-stimulus ITPC will be associated with shorter RTs, indicating more efficient task execution. 2) The effect of pre-stimulus FS and SE on RT will be mediated by post-stimulus ITPC, forming a neural pathway linking thought dimensions to behavioral performance.

By testing these hypotheses, the study aims to uncover how thought states influence cognitive performance through phase-based neural dynamics, bridging the gap between spontaneous thought, neural preparation, and task execution.

STUDY 1

Alpha and theta peak frequency track on- and off- thoughts

Published in:

Hua, J., Wolff, A., Zhang, J. *et al.* Alpha and theta peak frequency track on- and off-thoughts. *Communications Biology* 5, 209 (2022). https://doi.org/10.1038/s42003-022-03146-w

Abstract

Our thoughts change with high degrees of dynamic in their contents. At some points, our thoughts are related to external stimuli or tasks focusing on single content (on-single thoughts), While in other moments, they are drifting away with multiple simultaneous items as contents (off-multiple thoughts). Can such thought dynamic be tracked by corresponding neurodynamic?

Addressing this question, we track thought dynamic during post-stimulus periods by the EEG neurodynamic of alpha and theta peak frequency which, as based on the phase angle, must be distinguished from non-phase-based alpha and theta power. We show how, on the psychological level, on-off thoughts are highly predictive of single-multiple thought contents, respectively. Using EEG, on-single and off-multiple thoughts are mediated by opposite changes in the time courses of alpha (high in on-single but low in off-multiple thoughts) and theta (low in on-single but high in off-multiple thoughts) peak frequencies. In contrast, they cannot be distinguished by frequency power. Overall, these findings provide insight into how alpha and theta peak frequency with their phase-related processes track on- and off-thoughts dynamically. In short, neurodynamic tracks thought dynamic.

Key words mind wandering, peak frequency, alpha, theta, thought dynamic, on- and off-thoughts, phase-related processes, neurodynamic

Introduction

Our thought shows high degree of dynamic in its often changing contents. These contents include single thought contents like those related to a particular external task or stimuli, i.e., on-thoughts (Callard et al., 2013; Handy & Kam, 2015). In contrast, if we do not focus on the task, our thoughts may wander around multiple more internal contents holding simultaneously (rather than sequentially) in our mind. These are off-thoughts reflect one instance of mind wandering (Andrews-Hanna et al., 2014; Callard et al., 2013; Christoff et al., 2016, 2018; Fox et al., 2015; Seli, Kane, Smallwood, et al., 2018; Smallwood & Schooler, 2015; H. Wang et al., 2017) which we here take as 'special case of spontaneous thought that tends to be more-deliberately constrained than dreaming'(Christoff et al., 2016). The difference of on- and off-thoughts in their dynamic, i.e., pattern of change, on the psychological level raises the following question: Can the differential dynamic of on- and off thoughts on the psychological level be tracked by a corresponding dynamic on the neural level? Addressing this yet unresolved question is the goal of our investigation.

One influential hypothesis, the perceptual decoupling hypothesis (Barron et al., 2011; Schooler et al., 2011), assumes that off-thoughts are related to the decoupling of perception from external stimuli. The perceptual decoupling hypothesis concerns mainly the thought contents: if they are related to the presented stimulus or task, they are on-task and thus perceptually coupled (Barron et al., 2011; Schooler et al., 2011). If, in contrast, the thought content is not related to the stimulus or task, it is off-task and thus decoupled from the perception of the stimulus or task (Barron et al., 2011; Schooler et al., 2011). This raises the question of whether, at the psychological level, on- and off-task thoughts differ not only in content type but also in content quantity. Specifically, it remains unclear whether off-task thoughts involve holding multiple contents simultaneously, as opposed to a single content, as suggested by prior research (Mills et al., 2018). One would assume that on-thoughts are more likely related to single thought contents, i.e., one single item holding in one's mind. While off-thoughts may be accompanied by multiple thought contents holding simultaneously, i.e., multiple items kept in mind at the same time. Hence, on- and off-thoughts may be associated with different numbers of thought contents indexing differential thought dynamic, i.e., pattern of change. Thus, characterizing the thought dynamic of on- and off-thought in terms of their number of associated thought contents, i.e., single vs multiple, was the first specific aim of our study.

Is the differential thought dynamic of on- and off-thoughts on the psychological level of on- and off-thoughts mediated by a corresponding dynamic on the neural level, that is, neurodynamic? Tracking thought dynamic in the brain requires high temporal precision in order temporally relate the thought content to the timing of the external stimulus. That can be achieved by EEG which, unlike fMRI, provides high temporal resolution in the millisecond range. Various EEG studies reported different amplitudes in event-related potentials (ERP) like N100 and P300 (and other ERP's) during on- and off-thoughts (Baird et al., 2014; Baldwin et al., 2017; Broadway et al., 2015; Gonçalves, Rêgo, et al., 2018; Handy & Kam, 2015; Jin et al., 2019; Smallwood et al., 2008). More dynamic oscillatory measures highlight the involvement of alpha (Arnau et al., 2020; Baldwin et al., 2017; Braboszcz & Delorme, 2011; Brandmeyer & Delorme, 2018; Compton et al., 2019; Jin et al., 2019) and theta frequency bands (Atchley et al., 2017; Bocharov et al., 2019; Brandmeyer & Delorme, 2018; Gonçalves, Carvalho, et al., 2018; Jin et al., 2019; van Son, De Blasio, et al., 2019; van Son, de Rover, et al., 2019) during mind wandering. These findings raise the question whether dynamic changes in alpha and theta frequency power can track the thought dynamic of on- and off-thoughts with their potentially different number of thought contents, i.e., single vs multiple.

In addition to their power, neural activity in alpha and theta bands (and others) can be characterized by peak frequency sliding (FS) at specific points in millisecond time (Cohen, 2014b; Grandy et al., 2013; Mierau et al., 2017; Wolff, de la Salle, et al., 2019). As shown in both computational modelling and human EEG, increases in alpha peak frequency, i.e., the alpha oscillation speeds up (Cohen, 2014b), are directly related to increases in the input to the network and, on the more psychological level, to perception of specific contents (Cohen, 2014b). This is consistent with findings showing that higher cognitive load during externally-oriented tasks lead to higher alpha peak frequency. Given that cognitive load is related to the number of items holding in one's mind (37), alpha peak frequency may be taken as an index of the number of thought contents, i.e., single vs multiple, holding simultaneously in one's mind. We hypothesize that alpha peak frequency—and its temporal dynamics (i.e., frequency sliding or shifts over time) (Cohen, 2014b; Wolff, de la Salle, et al., 2019) —may serve as a candidate neural marker for tracking the number of thought contents. This effect is expected to be particularly relevant during on-task thoughts, which represent externally oriented cognition.

Unlike the well-studied alpha peak frequency, the theta peak frequency is less investigated. Recent studies associate it with multiple more internally-oriented thought contents as in depressive rumination or working memory (Wolff, de la Salle, et al., 2019; Wolinski et al., 2018). Moreover, theta peak frequency is supposed to stand in a specific relationship to alpha peak frequency with their harmonics facilitating processing of high cognitive loads with multiple thought contents (Rodriguez-Larios & Alaerts, 2019). Based on these findings, we hypothesize that theta peak frequency and its dynamic changes—specifically frequency sliding—may serve as a suitable neural marker for tracking the dynamics of off-task thoughts. As a form of internally oriented thought (Frömer et al., 2018; Kolvoort et al., 2020).

Using EEG, we apply a novel paradigm including neural, self-reported, and cognitive (accuracy) measures (Martinon et al., 2019; Smallwood & Schooler, 2015) (See Fig 1 for experimental overview), i.e., the Sustained Attention to Response Task (SART). We modified the standard SART in that we required participants to provide direct response to the target stimuli rather than, as in the standard version, holding their response. This allowed us to on-line explicitly specify the subjects' number of thought contents as single (rather than multiple) as they only had to press the button when the target stimuli were presented (but no standard and novel tones, see methods for details). Unlike in standard SART, this allowed us to also use reaction time as a behavioral maker. Note that the response was only required to target stimuli but neither to neglect standard and novel stimuli. The modified SART paradigm enabled us to measure alpha and theta peak frequency sliding during the post-stimulus period. The post-stimulus period captures the occurrence of on- and off-task thoughts prior to, and uncontaminated by, participants' judgments regarding the number of thought contents (see Fig 2 and Fig 3a).

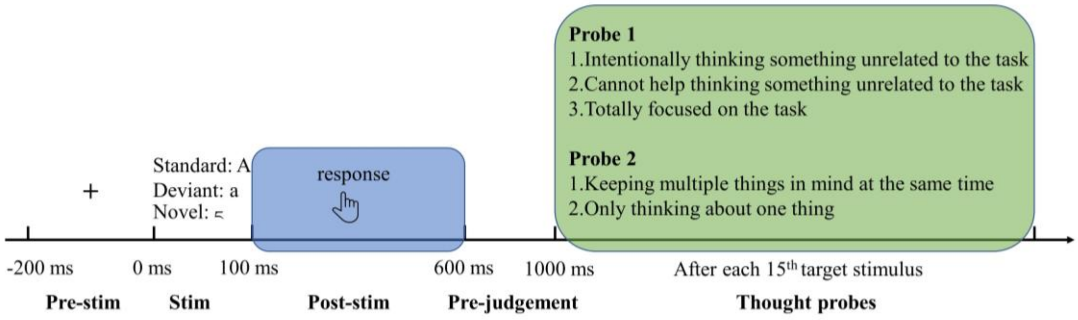


Fig 1 Experiment process and analysis schema. Experiment process: Each participant performed 1800 Sustained Attention to Response Task (SART) trials. In each trial, three types of stimuli were presented randomly for 100ms after 200ms fixation period: standard stimulus (upper case English letters), target stimulus (lower case English letters) and novel stimulus (letters from minority languages). Participants were requested to respond to the target stimuli by pressing the F key on the keyboard during the 900ms blank window following stimulus (post-stimulus period). After each 15th target stimulus two thought probes were shown, participants were asked to answer the probe questions based on their types of thoughts (on- vs off-task and single vs multiple contents).

Since our focus is on comparing different thought types in both their behavioral and neural (see below) correlates, we employed a novel way of analysing thought types, namely a trial-based analysis as distinguished from a subject-based analysis (Frömer et al., 2018; Kolvoort et al., 2020). A trial-based analysis doesn't average trials in each subject and do comparison among conditions on subject level, but take all trials into account. For that purpose, we statistically calculated a linear mixed model as that allows to control for inter-subject variation (Frömer et al., 2018; Kolvoort et al., 2020)**.**

Our first major finding consists in showing that, psychologically, on-thoughts are associated with single thought contents whereas off-thoughts include multiple thought contents holding simultaneously in one's mind. This suggests differential thought dynamic of on- and off-thoughts with respect to the number of their thoughts. The second major contribution of this study confirms our initial hypothesis: alpha and theta peak frequency track on-single and off-multiple thoughts in opposite directions. Specifically, on-single thoughts are associated with higher alpha FS and lower theta FS, whereas off-multiple thoughts exhibit lower alpha FS and higher theta FS.

Finally, it shall be noted that such distinction of the two types of thoughts could not be achieved when calculating alpha and theta power. Given that the only difference between alpha/theta peak frequency and power consists in the inclusion (peak frequency) and exclusion (power) of the phase angle (Cohen, 2014b; Grandy et al., 2013; Mierau et al., 2017; Wolff, de la Salle, et al., 2019), we assume that phase-related processes take on a key role in tracking the differential thought dynamic of on-single and of-multiple thoughts. Mechanistically, that extends the current neuro-computational population-based model of input-peak frequency relationship (Cohen, 2014b; Mierau et al., 2017) to the neuro-cognitive level by relating neurodynamical changes in alpha and theta peak frequency to changes in thought dynamic, i.e., on-single and off-multiple thoughts. Broadly, neurodynamic tracks thought dynamic.

Methods

Participants

Seventy right-handed adults participated in the study (32 female; age range = 18-29 years; mean age = 22.06 years, SD = 2.71 years). All had normal or corrected-to-normal vision and reported no neurological or psychiatric conditions that might affect performance. Of these, 9 were excluded as the data were not correctly recorded or got lost. Within these 61 subjects, 13 subjects whose 12 probe choices were all the same were excluded to ensure the validity of thought probes. After EEG preprocessing, 8 subjects were excluded for bad data quality (more than 50% epochs were excluded). Ultimately, 40 subjects' data were entered into final analysis.

The methods were performed in accordance with relevant guidelines and regulations and approved by the research ethics committee of the Nanjing Normal University, School of Psychology, and the study was carried out with their permission. Verbal informed consent was obtained from each participant prior to study participation.

Procedures

A three-stimulus Sustained Attention to Response Task (SART) was presented using E-Prime presentation software (version 2.10). We here used the standard SART for mind wandering (Cheyne et al., 2006; Christoff et al., 2009; Hester et al., 2005) which tests for subjects' thought probes, combined with the presentation of different stimuli including standard, target (deviant), and novel (as in Oddball paradigms, see Stimuli Information in Supplementary Materials for detailed information of stimuli). This paradigm served the purpose of explicitly specifying the subjects' number of thought contents as single (rather than multiple) as they only had to press the button when the target stimuli were presented (but no standard and novel tones).

Subjects were instructed to press the ‘F’ on the keyboard in response to the target stimulus and ignore the other two types. All participants had learnt English for more than 10 years and were unfamiliar with the languages which were used for the novel stimuli.

The ratio of presentation of the three stimuli, standard: target (deviant): novel was 8 : 1 : 1. All three stimulus types were presented randomly. Participants first completed 50 trials without thought probes as practice. The testing phase then consisted of 6 blocks of 300 trials each. The stimulus was presented for 100ms (stimulus period) after a fixation period of 200ms (pre-stimulus period), followed by a blank window of 900ms which, in the absence of judgment (see below), was labeled as the post-stimulus interval. The thought probes were presented at each 15th target stimulus, i.e., deviant stimulus. Since the latter were presented randomly (relative to novel and standard), timing and occurrence of the thought probes could not be predicted by the subjects (reflecting pseudo-random distribution of the thought probes).

In the thought probes, participants had to choose the answers according to their thoughts following the task stimulus they had just seen previously. Two thought features were focused on in this study: the process (off-thought or on-thought) and the number of contents (multiple contents or single content). These two features were taken as the first and second probe respectively in fixed order. Moreover, according to previous studies (Christoff et al., 2016) , participants may deliberately move their attention off the task. This can be explained as a thought state where deliberate constraints predominate over automatic constraints. As this state is different from mind-wandering (Christoff et al., 2016), we explicitly asked subjects to decide between deliberate off-thought and automatic off-thought in the first probe. Taken together, the thought probes amounted to the following (see also Fig 1a for the experimental design)

During the previous task, you were:

Probe 1:

1.Intentionally thinking something unrelated to the task

2. Cannot help but think about something unrelated to the task

3.Totally focused on the task

Probe 2:

1.Keeping multiple things in mind at the same time

2.Only thinking about one thing

After the 3rd block an emotional induction video was played in order to induce either joy or neutral emotion. Videos come from the Chinese Emotional Visual Stimulus (CEVS) (neutral emotion induction: duration: 2 min 17 s, from the movie ‘Computer Repair’; joy induction: duration: 2 min 23 s, from the movie ‘a big potato’) (Xu et al., 2010). Participants were asked to complete the Positive and Negative Affective Schedule (PANAS) (Watson et al., 1988) before and after the emotional induction. However, as there was no significant difference of RT and accuracy between before and after emotional induction in all thought types by applying LMM and GLMM (all $p > 0.05$), emotion was not taken into consideration in this study. To increase the number of trials for both behavioral and neural analyses, we included all trials in all subsequent analyses.

Before the formal experiment, participants were firstly instructed into a training session which contained 40 standard stimuli, 5 target stimuli, 5 novel stimuli and 1 thought probes. Subjects were guided through the whole paradigm and thought probes, if they have any questions they could go through the training session again, and they could only go into the formal experiment if they have no further questions about the paradigm.

Behavioral Analysis

To capture the moment to moment dynamic of thought, the analysis in this study was trial-based across subjects. The number of trials of conditions are shown in table 1. The response time (RT) was the interval between stimulus onset and participants’ responses. Differences in RT between conditions, i.e., the four different thought types, were analysed using linear mixed model (LMM).

We also analysed the differences in accuracy of responses. As the accuracy is not a continuous variable, LMM is not appropriate. We first define accuracy as the number of correct responses between each of the two thought probes, and then calculated the generalized linear mixed model where Poisson distribution assumption was chosen.

It was mainly focused on thought states, i.e. off-task or on-task in this study in probe 1, so the first and second choices in probe 1 were combined together as ‘off task’. The probe 2 focused on the amount of thought content in participant’s mind. The contingency table of the trial numbers of each condition were shown in table 1, based on which chi square analysis was conducted to explore the relationship between probe 1 and probe 2.

EEG recording and preprocessing

EEG data was collected from a 129-channel EEG system (HydroCel Geodesic Sensor Net, EGI System 300; Electrical Geodesic Inc., OR, USA) at a sampling rate of 1000 Hz and recorded with NetStation Software (Version 4.5.1, Electrical Geodesic Inc., OR, USA). Electrode Oz was used as the online reference. The impedance for all electrodes was kept below 50 kΩ while the data was recorded.

The data preprocessing was conducted using EEGLAB toolbox (Delorme & Makeig, 2004) (http://sccn.ucsd.edu/eeglab/) which is a freely available, open source MATLAB-based package for EEG data analysis. The EEG signals were re-referenced off-line to the average of the left and right mastoids. The signals were band-pass filtered between 1 and 60 Hz using a zero-phase finite impulse response (FIR) filter implemented in EEGLAB (Delorme & Makeig, 2004). Filtering was performed with EEGLAB's default FIR filtering routine (pop_eegfiltnew), which applies a Hamming-windowed sinc FIR filter. The filter was applied in a two-pass (forward–backward) manner to eliminate phase distortions. Filter order was automatically determined by EEGLAB as a function of the transition bandwidth and sampling rate, ensuring sufficient stopband attenuation while minimizing temporal ringing. To suppress line noise, a band-stop (notch) FIR filter between 46 and 54 Hz was applied using the same zero-phase Hamming-windowed sinc FIR framework. Following filtering, the data were resampled to 500 Hz using EEGLAB's anti-aliasing resampling procedure, which includes an internal low-pass FIR filter prior to downsampling to prevent spectral aliasing. The data was then epoched from -200ms to 1000ms to the stimulus onset without baseline correction. The bad epochs during which the data quality is significantly worse than nearby epochs were rejected according to visual inspection. Participants with more than 50% of their epochs rejected were not included in subsequent analyses. All stationary artifacts, specifically eye movements (blinks and saccades), were reduced using Independent Component Analysis (ICA) and Principle Component Analysis (PCA) by the EEGlab toolbox.

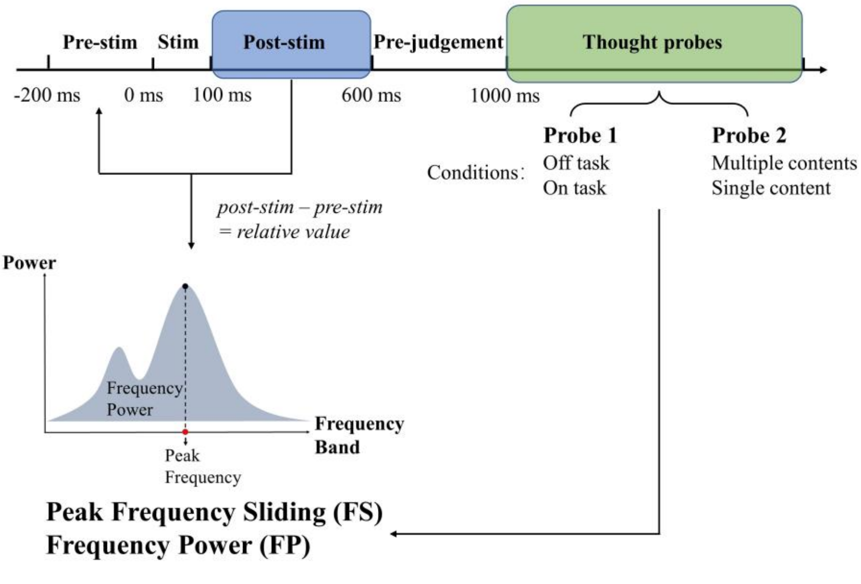


Fig 2 EEG analysis schema. EEG signals were first transferred to peak frequency sliding (FS) and frequency power (FP), then the average of pre-stim period (-200 – 100ms) was subtracted from post-stim period (100 – 600ms) to obtain the relative values. Alpha (8-13Hz) and theta (5-

8Hz) post-stim relative values were compared between conditions, i.e., the different thought types, using independent T-test.

Statistical Analysis

To investigate how momentary thought states relate to behavior and neural dynamics, we focused on trial-level variability rather than subject-level averages. Subject-based analyses primarily capture stable inter-individual differences, whereas our theoretical focus was on transient, state-dependent fluctuations of thought and their immediate behavioral and neural consequences. A trial-based framework therefore provides the appropriate temporal resolution to examine thought dynamics. The total trial numbers of each condition, i.e., thought probes, are shown in table 1. The trials with target stimuli which are just prior to thought probes were taken into analyses. After epoch-rejections, we have 286 trails for off-task, 156 trials for on-task, 227 for multiple-contents, 215 for single-content, 221 trials for off-multiple, 150 trials for on-single went into analysis. To ensure probe answers truly reflected participants' thoughts, only the data from those who didn't choose the same choices in subsequent probes across all trials were included in all other analyses. T-tests and ANOVAs were done in SPSS (version 21). The joint entropy analysis was done in python by using entropy_estimators toolboxe (version 0.0.1). As pointed out in the introduction, our primary focus was on comparing thought types irrespective of inter-subject differences. Because trial-based analyses inherently pool data across participants, it is necessary to explicitly model inter-individual variability. Linear mixed-effects models (LMMs) and generalized linear mixed models (GLMMs) allow us to assess condition effects while controlling for subject-specific baselines via random intercepts, thereby isolating thought-related effects from stable individual differences(Frömer et al., 2018; Kolvoort et al., 2020). The differences between conditions for both behavioral and EEG analysis were analysed by Linear mixed model (LMM) or generalized linear mixed model (GLMM, only for the accuracy analysis). All the LMM analyses treat random intercepts for participants as random effects. Both LMM and GLMM were done in R by using lmerTest package.

Definition of accuracy and response time (RT)

The probe questions were presented after each 15th target stimulus, thus between each two probes there were 15 responses. The accuracy was defined as the number of correct responses within these 15 responses. In behavioral analysis, the accuracy for each thought type was calculated by the answers to the thought probes following these 15 responses.

RT was defined as the time period between stimulus onset and participants' response to target stimuli.

The differences of accuracy between conditions were analysed by the GLMM for which the Poisson distribution assumption was chosen. The differences of RT were analysed by the LMM. In both GLMM and LMM the conditions (off-thought vs on-thought, multiple content vs single content, off-multiple vs on-single) were taken as fixed effects and the random intercepts for participants were modeled as the random effect. The relationship between probes were analysed by Chi square analysis.

Event- related potential (ERP)

Event-related potentials (ERPs) were analyzed to examine whether classic stimulus-locked neural responses differentiate thought states at early sensory and later cognitive processing stages. Including ERP analyses provides a benchmark against well-established EEG markers of perception and attention, allowing us to determine whether thought-related effects observed in phase-based measures are also reflected in conventional power-based evoked responses. Two ERP components were identified, which were N1 and P3. The mean amplitudes of these components were taken within the following windows: N1 (0 – 200 ms), P3 (200 – 500 ms). The mean amplitudes were then compared between off-multiple and on-single on both electrodes Fz and CPz respectively by applying the LMM. The conditions (off-multiple vs on-single) were taken as the fixed effect and the random intercepts for participants were taken as the random effect.

Peak Frequency Sliding (FS) and Frequency Power (FP)

To test whether thought-related neural differences are driven by changes in oscillatory speed or by changes in oscillatory amplitude, we quantified both peak frequency dynamics using frequency sliding (FS) and oscillatory power using frequency power (FP). FS captures moment-to-moment changes in the speed of neural oscillations, whereas FP reflects the magnitude of oscillatory activity. Comparing these two measures allows us to dissociate phase-based temporal dynamics from amplitude-based neural effects.

Following our hypotheses (see above), we focused on alpha (8-13 Hz) and theta (5-8 Hz) frequency bands, measuring both their peak frequency change with frequency sliding (FS) and their power change (FP) (Cohen, 2014b; Mierau et al., 2017; Rodriguez-Larios & Alaerts, 2019; Wolinski et al., 2018). According to the difference map of FS (Jia et al., 2017), the Fz electrode was chosen for FS and FP in alpha and CPz was chosen for theta (Fig 4A).

All preprocessed EEG data were first epoched to 1500 time points (-1000ms – 2000ms) to avoid the edge effect. The FS and FP were calculated according to the method of MX Cohen (Cohen, 2014b). The preprocessed data were first FIR bandpass filtered with 15% transition zone added to each edge of the filter range by applying the FIR filter implemented in EEGLAB, then a Hilbert transform was done after which the phase angle timeseries was extracted. The FS is the first derivative of the phase angle timeseries and a median filter with a window size of 10 time points was applied in order to reduce the non-physiological noise (Cohen, 2014b). For the FP, the analysis was the same as for the FS with only one difference: the modulus of the Hilbert transform was extracted rather than the phase angle timeseries. After FS and FP calculation, the average of pre-stim (-200ms – 0ms) were subtracted from all time points (-200ms – 1000ms) to get the values relative to the pre-stimulus period. The period from 600ms to 1000ms were taken as pre-judgement and excluded from analysis as in both off-multiple as well as on-single conditions more than 90% responses were made before 600ms. Then the post-stim relative values (100ms - 600ms) were extracted for alpha/theta FS and FP. Then the differences of FS and FP between the different thought conditions were analysed by applying the LMM as the analysis was trial-based. In the LMM modeling, the conditions (off-thought vs on thought, multiple content vs single content, off-multiple vs on-single) were taken as the fixed effect and the random intercepts for participants were taken as the random effect.

Dynamic Time Warping (DTW)

On the psychological level we tested whether on- and off-thoughts predict single and multiple thoughts. In order to probe the analogous prediction on the neural level, we used dynamic time warping (DTW). This was done to compare the time course of alpha/theta FS between the different thought types, i.e., on-single and multiple-off (and all other possible constellations).

DTW is a tool to compare different time series in terms of their mathematical distances such as Euclidean distance (H.-C. & Jansen, 1985). While DTW has previously been applied to EEG signals (H.-C. & Jansen, 1985), we here, for the first time, use DTW to compare the data from different frequency bands (alpha and theta) in the time domain, i.e., alpha/theta FS and FP. In this study, the time series being measured is -200ms - 1000ms alpha/theta FS values. To compare the time course mathematical distances of alpha/theta FS (and FP) among conditions, firstly, 150 trials were randomly extracted and averaged across all trials at each timepoint to yield one alpha/theta FS (or FP) time series for each condition. This provided the basis for applying DTW. Secondly, this process was repeated 150 times to get 150 DTW values for each pair of conditions (off-multiple, off-single, on-multiple, on-single). Then, the two way ANOVA was applied, after which Tukey's multiple comparisons test were conducted (Fig 5A, Table 3).

The Determination of alpha-theta peak frequency's 'harmonic locking'

Different frequency bands usually represent different cognitive functions (Kopell et al., 2010). The synchronization between distinct rhythms is a core mechanism to integrate neural systems at different spatiotemporal scales (Canolty & Knight, 2010; J. M. Palva & Palva, 2018). A recent study demonstrated that a 2:1 harmonic relationship between alpha and theta peak frequency is related to their higher synchronization and more efficient cognitive performance in participants (Rodriguez-Larios & Alaerts, 2019). To do this analysis, the proportion of time-points in which the alpha–theta peak ratio equaled 2.0 (henceforward termed "harmonic locking") was determined for each electrode, trial, and condition (Rodriguez-Larios & Alaerts, 2019). We then compared the proportions between off-multiple and on-single thoughts on electrodes Fz and CPz. We chose these electrodes to analyze the alpha and theta FS respectively.

Joint Entropy

Joint entropy is a measurement from information theory, it is a measure of the uncertainty of a set of variables (in our case 2 variables as alpha and theta peak frequency) (Baseer et al., 2017). While mean values of neural measures capture central tendencies, they do not characterize the variability or uncertainty of neural dynamics across trials. Joint entropy provides a principled way to quantify the uncertainty of the joint distribution of alpha and theta frequency dynamics, allowing us to assess whether different thought states are associated with more or less stable cross-frequency neural configurations. The function of joint entropy is: $H(X,Y) = -\sum_x \sum_y P(x,y)\log_2[P(x,y)]$, where x and y are particular values of X and Y, and P(x, y), is the joint probability of specific degrees in their values occurring together. Thus, joint entropy can be taken as a description of a joint probability distribution: the larger the entropy, the larger the uncertainty and lower the probability of specific values a particular variable can take on over multiple trials.

In this study, the joint entropy was used to describe the uncertainty of the changes in alpha/theta FS (and FP) during the post-stimulus interval (relative to the pre-stimulus period). The average of the post-stimulus period alpha/theta FS (and FP) relative changes in each trial were calculated for all trials, and then averaged across trials. The joint entropy was calculated on the joint distribution of alpha and theta values. Firstly, 150 trials were randomly chosen from each condition (off-multiple, on-single) by bootstrapping to calculate one entropy value for all these 150 trials. This process was repeated 1000 times. This allowed us to compare the joint entropy values between conditions (i.e., the different thought types) using independent T-tests (Fig 6C). The joint entropy was computed by the entropy_estimators toolkit (version 0.0.1) available in python, which provides a tool to calculate the joint entropy of continuous multi-variables from the determinant of the multivariate normal distribution. Finally, to compare the differences between conditions for alpha/theta FS (and FP), the differences (calculated by the subtraction between the entropies of chosen conditions) were normalized to z-scores. The independent T-tests were then applied.

EEG analysis – statistical analyses

In the EEG analysis, All the ERP, FS and FP analyses on alpha were done on the electrode Fz while for theta we took CPz according to the FS differences in the topographic maps (the difference between FS of off-multiple and FS of on-single, see Fig 4A). For the ERP's, the LMM were applied on two components comparing off-multiple and on-single: N1 (0-200 ms) and P3 (200 – 500 ms). The amplitude of these components was taken as the mean of each time periods. For FS and FP, the LMM was applied on the average of post-stimulus values relative to the pre-stimulus interval (100ms – 600ms) between conditions (e.g. off-thought vs on-thought, Fig 2). After that, the correlation was applied for probing the relationship of ERP components and FS. To do this, the FS and ERP values were first standardized by z-score within each subject, then the linear correlation was applied for all the trials. Furthermore, the peak frequency sliding (FS) and frequency power (FP) absolute values from -200ms to 1000ms were taken as a time series and the dynamic time warping (DTW) was applied to get the distance between conditions (Fig 5).

The independent T-test was also applied on FS entropy values to explore the difference of distributions between off-multiple and on-single. (Fig 6).

See supplement material for detailed information of analysis

Table 1. The Total Trial Numbers of Each Condition

Probe 1	Probe 2	
	Multiple content	Single content
Off task	239	76
On task	7	158

Table 1. The first and second choices in probe 1 were combined together as ‘off task’ while the third was taken as ‘on task’. The first and second choices in probe 2 were taken as ‘multiple contents’ and ‘single content’ respectively.

Results

Behavioral results – thought dynamics

Accuracy and RT are standard behavioral indexes of cognitive performance in mind-wandering like the SART paradigm (Cheyne et al., 2006; Hester et al., 2005). First, we show no significant difference between off-multiple and on-single in both task-related accuracy and RT, as well as between off task and on task, multiple-contents and single-content (RT: off-multiple v.s. on-single: t = -0.30; on task v.s. off task: t = -0.35; multiple-contents v.s. single-content: t = -0.45, CR: off-multiple v.s. on-single: z = 0.38; on task v.s. off task: z = 0.21; multiple-contents v.s. single-content:

z = 0.71, all $p > 0.05$, see Fig 3B, supplementary figure 1).

Second, according to previous studies, the state of 'mind-wandering' can be characterized by off-thoughts, i.e., 'off task' which was detected by probe 1 and 'multiple content' which was detected by probe 2 (Christoff et al., 2016, 2018). We applied both independently and conducted fitting chi square analysis to probes whether on- and off-thoughts can predict the occurrence of single and multiple thoughts. Our results show that the two probes are highly correlated (both $p < 0.0001$): when the first and second choices in probe 1 was chosen (off task), participants were much more likely to choose the first choice in probe 2 (multiple-contents).

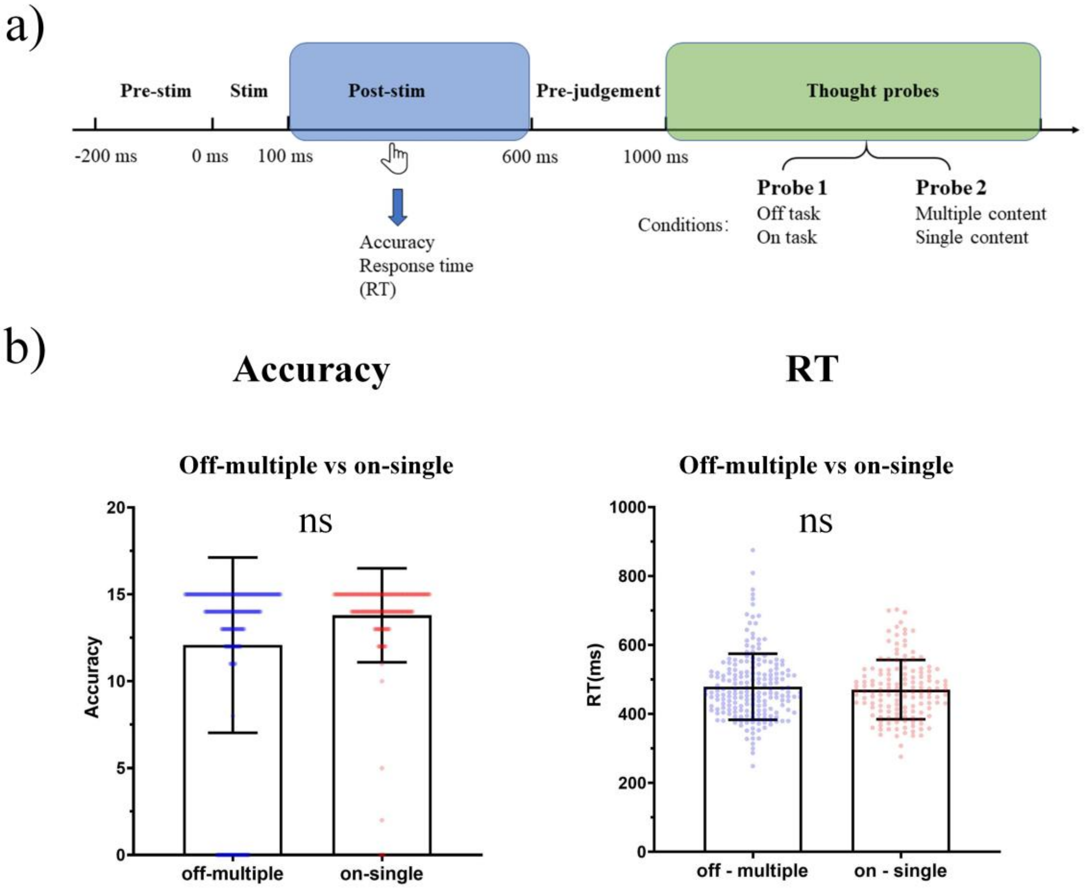


Fig 3 Behavioral analysis schema and results. a) Analysis schema: Data analysis was trial-based across subjects. The accuracy, response time (RT), and probe answers were taken into behavioral analysis. All trials were divided into different conditions according to probe answers: off-thought vs on-thought based on the first probe, multiple-contents vs single-content based on the second probe, off-multiple vs on-single based on the combination of the first as well as second probe. Mann Whitney U-test was applied on accuracy and RT between conditions. Chi square analysis was applied between two probes. b) Results of LMM on the accuracy and RT between off-

multiple and on-single. There were no significant differences between off-multiple and on-single on accuracy or RT. The error bar means SD; ns: no significance

The Neurodynamics of different thought states

We conducted a linear mixed model on ERP components (N1 and P3) to probe whether these components are significantly different between the different kinds or types of thoughts (see methods for details). The results show no significant differences between on-single and off-multiple thoughts in either N1 or P3 components (N1 on Fz: t = -1.74, p = 0.082; N1 on CPz: t = -0.93, p = 0.353; P3 on Fz: t = -1.54, p = 0.125; P3 on CPz: t = -0.56, p = 0.575; See supplementary figure 4).

Next, we investigated peak frequency in a time-resolved way, i.e., frequency sliding (FS) in both alpha and theta bands which, following the protocol by Cohen (37), is based on the phase angle (as calculated with Hilbert transform (37)). Additionally, we calculated the frequency power (FP) in both theta and alpha; the only difference of FP and FS is that the latter includes the phase angle which is eliminated from the former by taking the modulus of the phase (37). In short, peak frequency is phase-based whereas frequency power is not.

We first tested whether there were significant differences in peak frequency sliding (FS) and frequency power (FP) between the different thought conditions. In order to avoid carry-over effects of pre-stim values (-200 – 0ms), we subtracted the FS and FP values in the task-free post-stimulus interval (where the spontaneous thoughts occur) from their respective values in the pre-stim period. According to the topographical differences between the FS of off-multiple and on-single thoughts, the electrode Fz was chosen for all subsequent analyses on alpha while CPz was chosen for all subsequent analyses on theta (Fig 4A). The results show that FS in alpha band is significantly higher in on-task, single content and their combination (on-single thoughts) compared to off-task, multiple contents, and off-multiple thoughts. In contrast, FS in theta band showed the opposite results (off-multiple v.s. on-single alpha: t = 2.96, p = 0.003; off task v.s. on task alpha: t = 2.93, p = 0.004; multiple content v.s. single content alpha: t = 2.72, p = 0.007; off-multiple v.s. on-single theta: t = -2.08, p = 0.039; off task v.s. on task theta: t = -1.89, p = 0.060; multiple content v.s. single content theta: t = -2.05, p = 0.041; Fig 4B; supplementary figure 2). Unlike FS, FP did not yield such differentiation between the different thoughts. Only theta but not alpha frequency power showed significant difference between conditions (off-multiple v.s. on-single alpha: t = -0.97, p = 0.333; off task v.s. on task alpha: t = -1.06, p = 0.288; multiple content v.s. single content alpha: t = -0.44, p = 0.658; off-multiple v.s. on-single theta: t = -1.87, p = 0.062; off task v.s. on task theta: t = -1.52, p = 0.129; multiple content v.s. single content theta: t = -1.64, p = 0.101; Fig 4B, supplementary figure 2).

In the next step, the correlations between FS (both alpha on Fz and theta on CPz) and the amplitudes in the ERPs (N1 and P3 on both Fz and CPz) were estimated. As shown in Table 2, no significance was obtained and all R^2 values were rather low (<0.1, see Table 2).

Following Rodriguez-Larios and Alaerts (Rodriguez-Larios & Alaerts, 2019), we analysed the degree of synchronization, i.e., harmony, of alpha and theta FS. The results show that on-single thoughts do not exhibit a significantly higher degree of alpha theta peak frequency harmonic than off-multiple thoughts (on Fz: $t = 0.19$, $p = 0.852$; on CPz: $t = 1.03$, $p = 0.305$; supplementary figure 3).

Finally, to explore frequency ranges beyond theta and alpha, we also analysed the FS on delta (3 Hz – 4 Hz) and gamma (30 Hz – 40 Hz) on both Fz and CPz electrodes. The results show that neither delta nor gamma has significant difference between off-multiple and on single thoughts on both Fz and CPz electrodes (gamma Fz: $t = 0.71$, $p = 0.476$; gamma CPz: $t = 0.91$, $p = 0.362$; delta Fz: $t = -1.06$, $p = 0.300$; delta CPz: $t = 0.41$, $p = 0.684$; see supplementary figure 5).

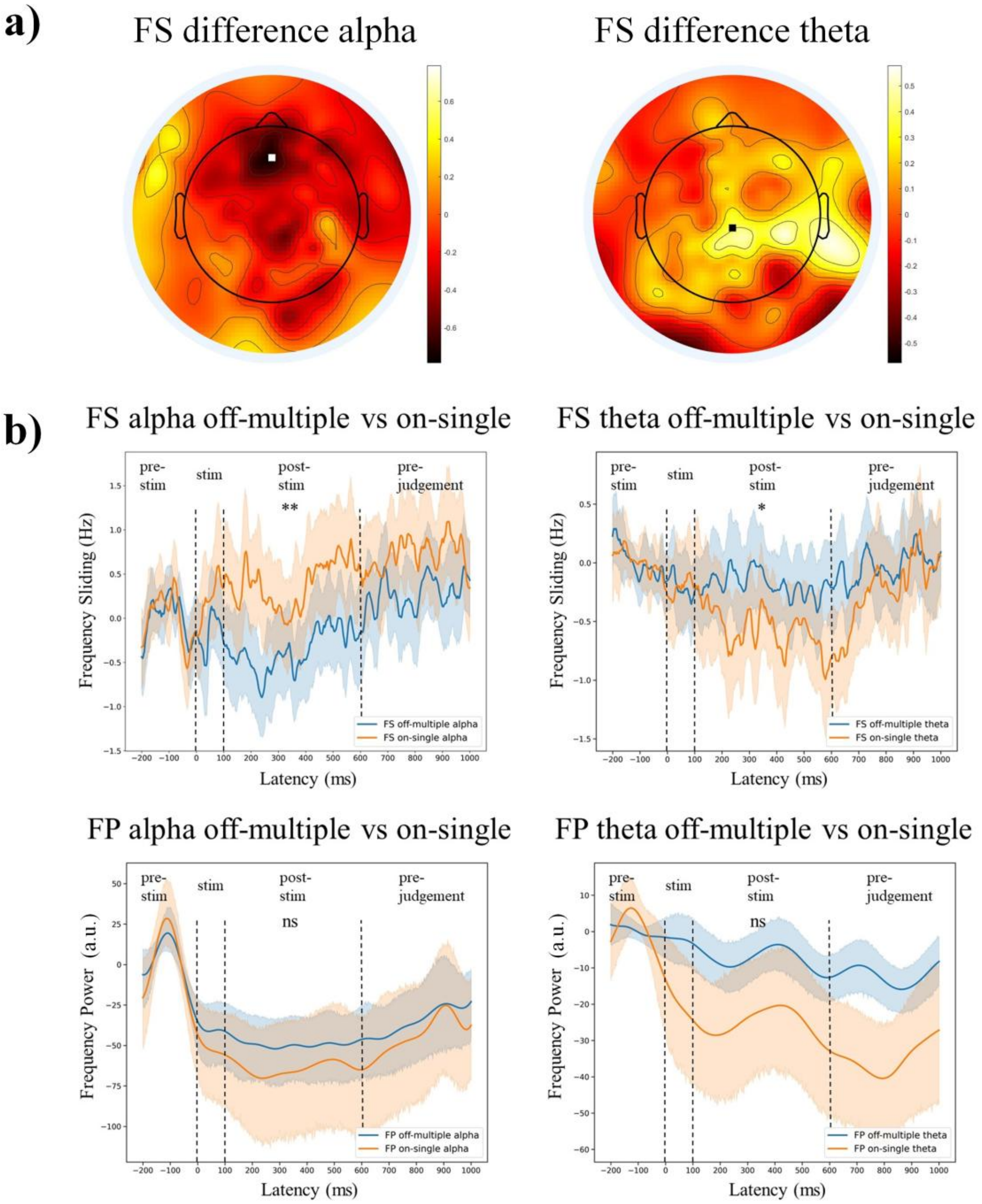


Fig 4 Frequency sliding (FS) and frequency power (FP) during different thought types. a) The difference map of FS post-stimulus' relative values. The difference map is calculated by subtracting on-single values from off-multiple values. According to visual inspection showing the strongest changes of FS, Fz was chosen for alpha FS and FP, CPz was chosen for theta FS and FP. b) The time series of FS and FP relative values (subtracting the average of -200 – 0ms from all time points) under each condition (off-multiple and on-single) with the results of LMM of post-stim relative values between off-multiple and on-single. Significant differences were found

between off-multiple and on-single thoughts in both alpha and theta FS but not in FP. *: $p < 0.05$; **: $p < 0.01$; ns: no significance

Table 2. Results of the correlation between ERPs and FS

	FS alpha (Fz)				FS theta (CPz)			
	Beta values	95%CI	p value	R^2	Beta values	95%CI	p value	R^2
N1 Fz	-0.049	-0.15 – 0.05	0.351	0.002	-0.042	-0.06 – 0.14	0.422	0.002
N1 CPz	-0.079	-0.18 – 0.02	0.127	0.006	0.037	-0.07 – 0.14	0.480	0.001
P3 Fz	-0.014	-0.12 – 0.09	0.782	<0.001	-0.027	-0.13 – 0.08	0.603	<0.001
P3 CPz	-0.003	-0.11 – 0.10	0.947	<0.001	-0.001	-0.10 – 0.10	0.990	<0.001

Table 2. The correlations between FS (both alpha on Fz and theta on CPz) and the amplitudes in the ERPs (N1 and P3 on both Fz and CPz) were estimated by using linear mixed model. No significance was found. Note. FS: frequency sliding; ERP: event-related potentials.

The neurodynamic distances between different thought states

Following our behavioral data, off-thoughts are related to multiple contents while on-thoughts are rather associated with single content. In order to test their relationship on the neuronal level, we compared the alpha and theta FS timeseries' associated with the different thoughts by utilizing dynamic time warping (DTW). The DTW is a measure for comparing the similarity between two time series. This allowed us to directly compare the temporal structure of two alpha/theta FS time series during on-thought FS with, for instance, the one during single content FS (and the same, analogously for all the comparisons among the four thought conditions). As is shown in table 3, all interaction effects are significant (all $p < 0.0001$). The results show that in both alpha and theta peak frequency bands, the distances in the alpha/theta FS time series of on-thought vs single content are significantly lower than the ones of on-thought vs multiple contents and of off-thought vs single content (all $p < 0.0001$, Fig 5A, table 3, table 4). This result is the same for FP time series except FP alpha which does not show significant difference between off-single and on-single (all significant $p < 0.0001$; FP alpha off-single vs on-single: $p = 0.856$ Fig 5A, table 3, table 4). The same holds for off-thought and multiple contents in both alpha and theta FS and FP. Hence, the DTW analysis supports the assumption of a close neurodynamic relationship of on-thoughts with single contents as well as of off-thoughts with multiple contents on the neuronal level (Fig 5B).

Table 3. the ANOVA results of DTW

	FS alpha		FS theta		FP alpha		FP theta	
Variance source	F	p	F	p	F	p	F	p
probe 1	0.12	0.724	0.83	0.361	72.80	<0.0001	16.50	<0.0001
probe 2	0.37	0.544	8.54	0.004	0.47	0.493	0.15	0.699
probe 1 * probe 2	421	<0.0001	105.5	<0.0001	93.29	<0.0001	331.4	<0.0001

Table 3. The ANOVA results of DTW Firstly, 150 trials were randomly extracted and averaged across all trials at each timepoint to yield one alpha/theta FS (or FP) time series for each condition. Secondly, this process was repeated 150 times to get 150 DTW values for each pair of conditions (off-multiple, off-single, on-multiple, on-single). Then, two way ANOVA was applied. The result show that all interaction effects are significant.

Table 4. Adjusted p values of multiple comparison on DTW

		FS alpha		
	off-multiple	**off-single**	**on-multiple**	**on-single**
off-multiple		<0.0001	<0.0001	ns
off-single			ns	<0.0001
on-multiple				<0.0001
on-single				
		FS theta		
	off-multiple	**off-single**	**on-multiple**	**on-single**
off-multiple		<0.0001	<0.0001	ns
off-single			0.0406	<0.0001
on-multiple				<0.0001
on-single				
		FP alpha		
	off-multiple	**off-single**	**on-multiple**	**on-single**
off-multiple		<0.0001	<0.0001	<0.0001
off-single			<0.0001	ns
on-multiple				<0.0001
on-single				
		FP theta		
	off-multiple	**off-single**	**on-multiple**	**on-single**
off-multiple		<0.0001	<0.0001	0.0094
off-single			0.0472	<0.0001
on-multiple				<0.0001
on-single				

Table 4. After the two way ANOVA, the Tukey’s multiple comparisons test were conducted upon DTW values.

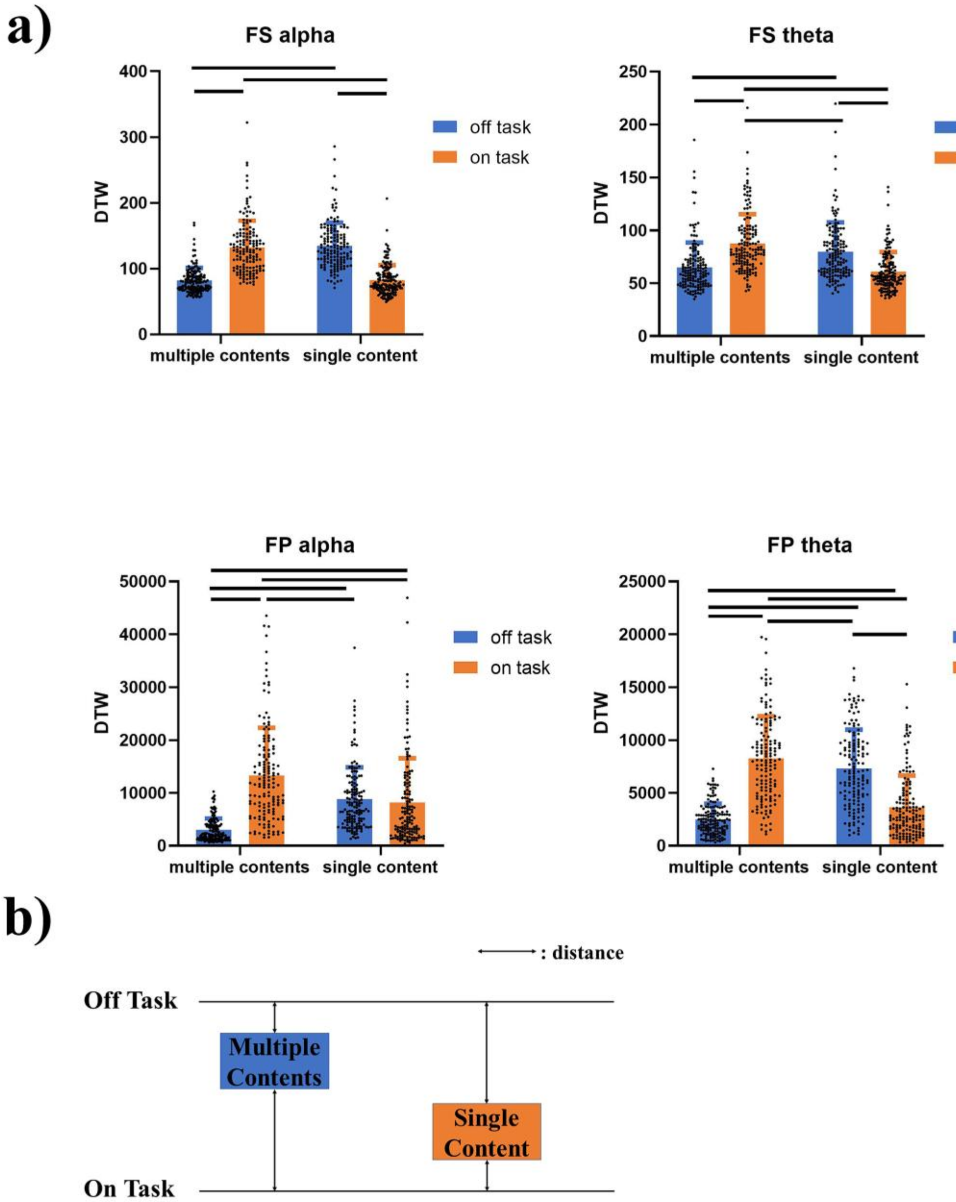


Fig 5 Results of FS and FP dynamic time warping (DTW). a) The result of FS and FP DTW. The distances between off-task and multiple-contents, on-task and single-content are the smallest on both alpha and theta FS. The lines mean there’re significant differences between groups. b) The schematic graph of the DTW result.

Different thought states show different degrees of uncertainty in their neurodynamic

In order to investigate the distribution of FS values in alpha and theta, joint entropy (JE), a measurement for describing the uncertainty of a set of variables, was applied to map their data distribution (Baseer et al., 2017). According to the joint distribution of alpha-theta FS, as measured by JE, off-multiple and on-single thoughts could be discriminated well by FS ($t = 46.42$, $p < 0.0001$). However, although the joint distribution of off-multiple and on-single thoughts is different from each other, the FS values of on-thoughts and single content are highly overlapped with the overall distribution or range of the ones for off-thoughts and multiple contents (Fig 6). Moreover, we can see that the range (or variance) of the data distribution, i.e., JE of FS for off-multiple thoughts is significantly higher than the JE of on-single thoughts (Fig 6).

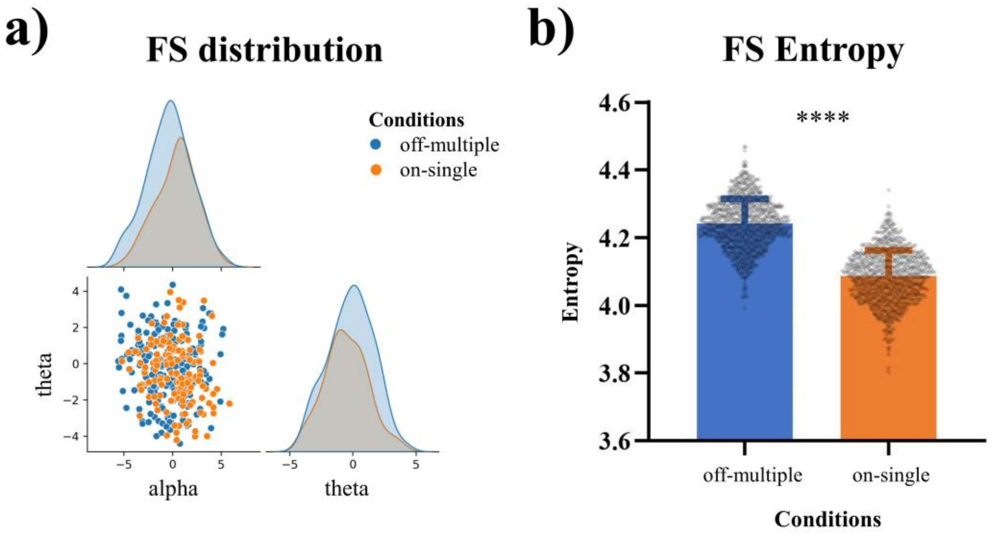


Fig 6 The joint distribution of FS alpha and theta and joint entropy (JE). a) The joint distribution of alpha/theta FS (and FP). Off-multiple and on-single's distribution could be discriminated in FS with overlaps. b) The joint entropy (JE) results in FS. JE values for off-multiple thoughts are significantly higher than those for on-single thoughts. The error bar means SD. ****: p<0.0001

Together, these results on joint entropy support again the good capacity of FS in distinguishing different thought types. Moreover, the results show that off-multiple thoughts exhibit a wider and more extensive data distribution, i.e., in FS than on-single thoughts. It shall be noted though that the data distribution of FS for on-single thought is included as more limited subspace with the more extended distribution of FC for off-multiple thought. That partial overlap of on-single FS values with the much larger range of off-multiple FS values suggest that the former may represent a subgroup of the latter.

Discussion

The goal of our study was to investigate how the psychological dynamic of on- and off-thoughts with respect to the number of their contents (one vs many) is tracked by a corresponding neurodynamic of alpha and theta peak frequency. Our results revealed that, on the psychological level, on-thoughts are associated with single content, namely those related to the stimulus or task, while off-thoughts include multiple thought contents holding simultaneously in one's mind. Importantly, this relationship was further supported at the neural level by the DTW analysis. The temporal structure of neural dynamics associated with on-thoughts was most similar to that observed during single-content thoughts. Conversely, off-thoughts showed the greatest temporal similarity to multiple-content thoughts. Together, these findings indicate that the close relationship between task-relatedness and content quantity is instantiated in shared temporal neural dynamics, providing converging evidence that neurodynamics track thought dynamics over time.

Neuronally, as measured in post-stimulus periods using EEG, the time course of on-single thoughts exhibited increasing alpha peak frequency and decreasing theta peak frequency (as measured by their frequency sliding) relative to pre-stimulus, while off-multiple thoughts showed the reversed pattern. Importantly, these thought-specific changes were only observed in the phase-angle–based measures of alpha and theta peak frequency, but not in their non–phase-based power. This dissociation was further supported by a series of complementary null findings. First, classic stimulus-locked ERP components (N1 and P3) did not distinguish between on-single and off-multiple thoughts, nor were their amplitudes significantly correlated with frequency sliding in either frequency band. These results suggest a key role of phase-related processes in tracking thought dynamic.

In addition, not all phase-related measures were sensitive to thought dynamics. Specifically, alpha–theta harmonic locking did not differ between thought conditions, indicating that the observed effects are not driven by general cross-frequency synchronization. Likewise, frequency sliding in delta and gamma bands did not show thought-specific differences. Together, these findings point to a selective role of phase-based peak frequency dynamics in alpha and theta bands, rather than a global phase effect across frequencies or metrics. This specificity strengthens the interpretation that alpha and theta frequency sliding capture a distinct neurodynamic mechanism underlying thought dynamics.

On- and off-thoughts show a specific dynamic as they are related to different numbers of thought contents. We observe higher association of on-thoughts with single content while off-thoughts are characterized by multiple simultaneous contents during one and the same trial. That is further supported by our finding that, applying chi square analysis, on-thoughts can reliably predict single contents while, analogously, off-thoughts predict multiple contents. Finally, the cognitive relevance of the differential number of contents is supported by higher task-related accuracy during both on and single thoughts when compared to off and multiple thoughts.

Together, our findings suggest that on- and off-thoughts are not only distinguished in the relation of their contents to the respective external stimulus but also in their number of contents, i.e., single vs multiple. Especially, the occurrence of multiple contents holding simultaneously in off-thoughts suggests their close relationship to internally-oriented cognition: as they are not related to the external stimulus, they must be generated internally rather than externally. One may consequently hypothesize that multiple simultaneously occurring thought contents may reflect ongoing processes of different forms of internally-oriented cognition like self-relatedness (Forster & Lavie, 2014; Fox et al., 2018), mental time travel (Northoff & Huang, 2017; Schacter et al., 2012), and emotional processes (Fox et al., 2018; Smallwood et al., 2009). That, however, warrants future investigation. Accordingly, our observation of multiple thought contents holding during specifically in association with off-thoughts reveals a thought dynamic that may connect them closely to the various forms of internally-oriented cognition.

Can the thought dynamic of on-single and off-multiple thoughts be tracked by a corresponding dynamic on the neuronal level? We reveal that peak frequency of alpha and theta show different dynamic patterns during on-single and off-multiple thoughts. Specifically, relative to the stimulus/pre-stimulus period, the time course of alpha peak frequency (as measured by frequency sliding) show a post-stimulus increase during on-single thoughts. In contrast, alpha peak frequency decreased during the post-stimulus interval when subjects reported off-multiple thoughts in the subsequent judgment. Compared to alpha peak frequency, the theta peak frequency exhibited the reverse pattern with post-stimulus increase in off-multiple thoughts and decrease in on-single thoughts. Together, these findings strongly suggest direct relationship of neurodynamic changes of alpha and theta peak frequency to a specific pattern of thought dynamics.

In addition, the joint entropy analysis provides important insight into the structure of thought dynamics. Although off-multiple and on-single thoughts could be statistically distinguished based on the joint distribution of alpha and theta frequency sliding, their distributions partially overlapped. This pattern suggests that on- and off-thoughts may not constitute strictly discrete mental states. Instead, on-task, single-content thoughts may reflect a more constrained and stabilized configuration within a broader and more variable space of off-task, multiple-content thoughts. From this perspective, off-multiple thoughts encompass a wider range of neurodynamic states, with on-single thoughts occupying a more restricted subregion of this space.

The role of specifically peak frequency, i.e., alpha and theta for on- and off-thoughts is further supported by our findings in both ERP and power. Neither the N1 nor the P3, averaged at stimulus onset, could not distinguish on-single and off-multiple thoughts. Even more important, we also calculated the power in alpha and theta frequency by eliminating the phase-related information through applying the modulus of the phase (37). Replicating previous studies, we did observe power changes in the post-stimulus period in both alpha (Arnau et al., 2020; Baldwin et al., 2017; Brandmeyer & Delorme, 2018; Compton et al., 2019; Jin et al., 2019) and theta frequency bands (Brandmeyer & Delorme, 2018; Gonçalves, Carvalho, et al., 2018; Jin et al., 2019; van Son, De Blasio, et al., 2019; van Son, de Rover, et al., 2019). However, extending beyond the previous findings, we demonstrate that these power changes remain thought-unspecific, i.e., they were similar for on-single and off-multiple thoughts.

Given that the only difference between alpha/theta peak frequency and power consists in the inclusion (peak frequency) and exclusion (power) of the phase angle (37), we assume a special role of phase-related process in tracking the differential dynamic of on-single and off-multiple thoughts. Our findings thus support the assumption that the neurodynamic of specifically alpha and theta peak frequency (rather than their power) allows tracking the differential dynamic of on-single and off-multiple thoughts possibly through phase-related processes (as these were eliminated in the power).

What are the mechanisms by which peak frequency tracks on-single and off-multiple thoughts? Peak frequency is related to specific processes on both neuronal and cognitive levels. Neuronally, it is related to the neuronal input driving action potentials and population network activity: the more neuronal input, the higher population activity, and the higher the peak frequency (Cohen, 2014b). At the same time, peak frequency in especially alpha is known to relate to single specific perceptual and cognitive contents: the higher the external perceptual or cognitive load, the higher alpha peak frequency (Cohen, 2014b; Gulbinaite et al., 2017; Mierau et al., 2017). Applied to our findings, this means that higher alpha peak frequency is most likely driven by increased neuronal input as related to the single external task-related contents of on-single thought.

How about off-multiple thoughts? Given that the off-thoughts are task-unrelated, i.e., off-task, the neuronal input must here be generated internally, that is, independent of the external input related to the stimulus theta (Axmacher et al., 2010; Moran et al., 2010; Wolinski et al., 2018). That is indirectly supported by the fact that in off-multiple thoughts, the external input did not yield any increase in alpha peak frequency which, as our data in on-single thoughts suggest, are related to the neuronal input yielded by the external stimulus. Instead of a decrease, we observed an increase in theta peak frequency during off-multiple thoughts. We propose that this increase reflects internally generated neuronal input. Such input is decoupled from external stimuli, consistent with the Perceptual Decoupling Hypothesis of mind-wandering (Baird et al., 2014; Barron et al., 2011; Handy & Kam, 2015; Schooler et al., 2011; Smallwood et al., 2008).

Together, we assume that both on-single and off-multiple thoughts are mediated by neuronal inputs on the population level which, on the systemic level, is manifest in peak frequency (37). While the difference between the two thought types consists in distinct origins or sources of their respective neuronal inputs, i.e., external and internal (Dixon et al., 2014), which is mediated by peak frequency in distinct bands, i.e., alpha and theta (Braboszcz & Delorme, 2011; Sharma et al., 2020). (see Fig

7).

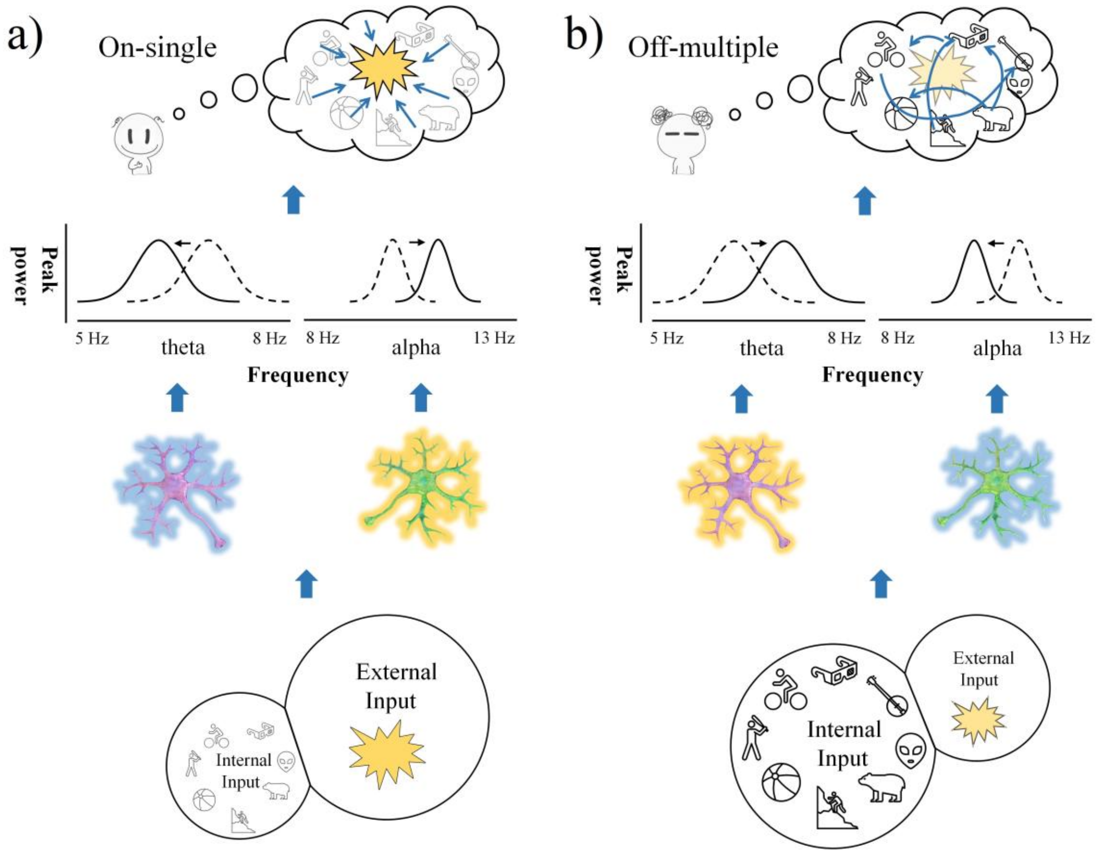


Fig 7 Schematic illustration of the proposed mechanisms mediating the relationship between neuronal input, alpha/theta frequency sliding and thought types. a) – on-single thoughts: Here during external tasks, the single external input (yellow) dominates, activates external-neurons on the population level (lower level of graph), increases alpha peak frequency, decreases theta peak frequency (middle level), and leads to the cognition of on-single thoughts (upper level). b) - Off-multiple thoughts. Here, multiple internal inputs dominate during external tasks (lower level) (blue), increase theta peak frequency, decrease alpha peak frequency (middle level), and are psychologically manifest as off-multiple thoughts (upper level)

Finally, our finding of thought-specific changes in alpha and peak frequency lends further support to and extends the different variations of process models of spontaneous thought proposed recently. These include (i) dynamic models which explains 'mind-wandering' in two dimensions of deliberate constraint and automatic constraint (Christoff et al., 2016; Kucyi, 2018; Kucyi et al., 2018), (ii) process model of spontaneous thought where 'mind-wandering' is represented by its off-task contents (Andrews-Hanna et al., 2018), (iii) process-occurrence framework where task-related ‘mind-wandering’ is conceived as an assemble of different experiences and thoughts (Callard et al., 2013; Seli, Kane, Smallwood, et al., 2018; H. T. Wang et al., 2018), and (iv) the Spatio Temporal Theory of spontaneous Thought (STTT) (Northoff, 2018). Our results support and extend these models as we show that off-task thought is associated with multiple contents. By demonstrating a relationship between neurodynamic and thought dynamics, our findings provide empirical support for the Spatio-Temporal Theory of Thought (STTT) (Kolvoort et al., 2020; Northoff et al., 2020a). In particular, they align with the recent extension of STTT, which proposes temporal dynamics as a shared feature—or “common currency”—across neuronal and psychological levels of thought (Kolvoort et al., 2020; Northoff et al., 2020a).

Methodological limitations

We applied a modified version of the SART that inserted a post-stimulus period with an immediate judgment on thought probes (rather than holding the judgment). This allowed us to directly test the neuronal changes in peak frequency prior to the single-trial judgment. While we tested for the relative changes in alpha and theta peak frequency during the post-stimulus interval compared to the stimulus/pre-stimulus periods, we can still not rule out carry-over effects from the latter to the former. These are rather unlikely, though, given that we observed changes in the neurodynamic of alpha and theta peak frequency in specifically the post-stimulus interval.

Moreover, due to the fact that the pre-stimulus period was rather short, we remain unable to investigate the impact of pre-stimulus changes on the post-stimulus interval. This may be necessary in the future though given recent studies that show how pre-stimulus changes affect stimulus-related and post-stimulus activity (Huang et al., 2017; Wainio-theberge et al., 2020). This may be of strong interest as we assume that multiple contents may also be mediated during the pre-stimulus activity period.

Further more, as we had only 12 thought probes for each subject to avoid too much interruptions and only the trials prior to each thought probe were taken, only 12 trials for each subject came into the analysis. These 12 trials were further divided into different groups (i.e., thoughts) according to the thought probes answers just after them. Thus the number for each subject under each condition is low. Although the LMM and GLMM were conducted, the low trials number may still be a limitation of this paper. Experiments with more trials will be conducted in the future.

Conclusion

Can the thought dynamic of our wandering mind with its on- and off-thoughts be tracked by a corresponding dynamic in our brain’s neural activity, i.e., neurodynamic? We demonstrate that, on the psychological level, on- and off-thoughts are associated with different numbers of thought contents, i.e., single and multiple. Next, we show how such thought dynamic is tracked by phase-based (Hilbert transform) alpha and theta peak frequency rather than their non-phase-based (modulus) power. Measured by frequency sliding, alpha and theta peak frequency exhibit opposite temporal changes during on-single and off-multiple thoughts.

Together, our results provide evidence that thought dynamic (number of thoughts), during both internally- and externally-oriented cognition (off-multiple and on-single thoughts) is tracked by phase-related processes as measured with theta and alpha-peak frequency. Mechanistically, that extends the input-based population model of alpha- and theta peak frequency (37) to the neuro-cognitive level by linking their phase-related processes to thought dynamic. More generally, our findings suggest that temporal dynamic is realized in seemingly corresponding ways on both psychological and neural levels of thought thus providing their hitherto missing link or "common currency" (Kolvoort et al., 2020; Northoff et al., 2020a). In short, we show how neurodynamic tracks thought dynamic.

STUDY 2

Dynamic fingerprints of thoughts: timescales distinguish thought orientation and task-relatedness

published in:

Hua, J., Ge, X., Dou, M., Zhang, Y., Ge, L., Fogel, S., Zhang, J., & Northoff, G. (2025). Distinct timescales dissociate spontaneous thought dimensions. Proceedings of the National Academy of Sciences, 122(38), e2427088122. https://doi.org/10.1073/pnas.2427088122

Abstract

Our spontaneous thoughts encompass various dimensions, such as task-relatedness (off vs. on task), and thought orientation (internal vs. external). However, their distinction remains unclear. Our study addresses this issue by focusing on their timescales at both the behavioral level (using fast and slow finger tapping) and the neural level (using EEG) using two independent datasets (N = 84 and 35). Behavioral results revealed a double dissociation: task-relatedness was linked to fast tapping only, whereas thought orientation was associated with slow tapping only. At the neural level, we assessed topographic similarity in EEG to quantify the temporal influence of past neural activity on current ones. Task-relatedness was associated with topographic similarity only during fast tapping, while thought orientation did so only during slow tapping. Critically, topographic similarity was phase-based, as shown by its correlation with phase-locking value and the loss of associations with thought after phase-shuffling. This indicates that the neural signatures of both thought dimensions are strongly phase-dependent. Finally, we demonstrate that nonlinearity plays a distinct role mediating the impact of different timescales (slow and fast finger tapping) on spontaneous thoughts at both behavioral (precision error) and neural levels (topographic similarity). Overall, these results demonstrate that task-relatedness is associated with short timescales, whereas thought orientation is associated with long timescales. This highlights how distinct temporal dynamics shape different spontaneous thought dimensions on both their behavioral and neural features.

Introduction

Humans exhibit a multitude of thoughts that are highly multidimensional. One dimension of thought, namely spontaneous thought, is commonly described as the experience of "mind wandering" (Christoff et al., 2016; Smallwood & Schooler, 2006). Mind wandering can include thoughts during a task that remain unrelated to the task at hand, *i.e.*, "off-task" thoughts. A wealth of functional brain imaging work has distinguished these from "on-task" thoughts. On- and off-task thoughts can thus be considered two ends of the spectrum of thought "*task-relatedness*". Yet another dimension of thought concerns the "*orientation"* of its content, that is, whether it is directed internally towards the self (*i.e.*, thoughts about events related to the inner self), or, externally towards the environment (*i.e.*, thoughts about features and events in the outer environment). Recent studies suggest that thought orientation and task-relatedness could be distinct dimensions, differing in their neural correlates and temporal dynamics (Kucyi et al., 2018; Rostami et al., 2022; Vanhaudenhuyse et al., 2011). The extent to which these dimensions are dissociable at the behavioral and neural levels in terms of their temporal structure and processing mechanisms remains unclear. Understanding the temporal and spatial dynamics of thought, and linking them at the neural and behavioural level will provide novel understanding of the temporal shaping of our thought in terms of their timescales. This would add additional support to what recently has been introduced as Spatial-Temporal Neuroscience (Northoff, Buccellato, et al., 2024; Northoff et al., 2020a, 2020b).

One fundamental and unresolved question about the nature of spontaneous human thought is whether off-task thoughts are equivalent to internally-oriented thoughts, and, on the other hand, whether on-task thoughts are equivalent to externally-oriented thoughts? Traditionally, the two dimensions of "task-relatedness" (on *vs*. off-task) and "thought orientation" (external *vs*. internal) thoughts were presumed as equivalent (Andrews-Hanna et al., 2010; Arnau et al., 2020; Bastian & Sackur, 2013). However, emerging empirical and neuroimaging evidence suggests a functional and anatomical dissociation between them, thus suggesting that they should be considered separately. For example, task-relatedness measures the extent to which one's thoughts are focussed on the task-at-hand (Barron et al., 2011; Christoff et al., 2016; Smallwood & Schooler, 2006), which can range on a continuum from completely focussed and engrossed in the task ("on-task"), to absent-minded, wandering thoughts ("off-task"). By contrast, thought orientation measures whether the thought content is focussed more on the external environment, or, at the other end of the continuum, focussed on the self, and thus, internally on one's own mental state (Baird et al., 2014; Kucyi et al., 2021; Schooler et al., 2011; Vanhaudenhuyse et al., 2011). Furthermore, the extremes of the spectrum of the task-relatedness and thought orientation dimensions suggest that they are dissociable in terms of their functional neuroanatomical differences in the recruited brain regions, *e.g.*, sensory *vs*. prefrontal regions, and their neuronal timescales, fast *vs*. slow (Kucyi et al., 2021; Rostami et al., 2022; Vanhaudenhuyse et al., 2011). Again, supporting the notion that these are separate dimensions. However, investigation directly comparing the two spontaneous thought dimensions remains to be conducted.

Given the yet unclear characterization and differentiation of task-relatedness and thought orientation, as potentially distinct thought dimensions, the goal of this study is to directly compare them to one another by investigating their inter-relationship and possible distinction in terms of both behavioral and neural correlates. Our focus is especially on their timescales which, broadly-speaking refer to the duration of the thought process that could be either longer, or shorter (Christoff et al., 2016, p. 2; Rostami et al., 2022). Based on previous findings (Kucyi et al., 2018; Rostami et al., 2022; Vanhaudenhuyse et al., 2011), we hypothesize that the two thought dimensions can be distinguished by their timescales, and thus by their durations at both the behavioral and neural level.

Potential differences in timescales between thought dimensions may offer a means to distinguish them at both the behavioral and neural levels. Prior work suggests that thought orientation (i.e., internal vs. external thoughts) unfolds over longer durations than task-relatedness (i.e., on-task vs. off-task thoughts), indicating a longer timescale for orientation compared to task-relatedness. Accordingly, these potential timescale differences may be useful to distinguish the two thought dimensions on both behavioral and neural grounds (Rostami et al., 2022; Vanhaudenhuyse et al., 2011). To examine this at the behavioral level, we employed the finger tapping paradigm, a widely used method for indirectly indexing ongoing thought through motor variability. Tapping variability has been shown to correlate with fluctuations in attention and mind-wandering: higher variability reflects off-task thought, while lower variability reflects on-task engagement (Groot et al., 2022; Kucyi et al., 2018; Petilli et al., 2018). Further, high variability of spontaneous finger tapping has been found to be associated with reduced attention, indicating off-task thought, whereas low variability in finger tapping relates to on-task thought (Groot et al., 2022). Moreover, variability can also serve as index of speed and thus timescales (Northoff, 2018). Therefore, we used the variability of slow and fast finger tapping to investigate the timescales of different thought dimensions. In this study, we used precision error (PE) to quantify tapping variability and investigate whether PE during slow and fast finger tapping, as a behavioral proxy of timescales, differentially correlates with thought dimensions. Specifically, we hypothesize that PE will be more strongly associated with task-relatedness during fast tapping—reflecting shorter timescales—and with thought orientation during slow tapping, which engages longer timescales.

What about the distinct neural correlates of task-relatedness and thought orientation dimensions? In terms of brain dynamics, timescales can be measured from how EEG activity at an earlier time point influences neural activity at later time point. This can be measured using "*topographic similarity*", which quantifies the resemblance between the topography at one time point with those at subsequent time points (Luo et al., 2024; Tian & Huber, 2008). More precisely, topographic similarity measures the extent to which the spatial configurations of EEG derivations at past time points influence their distribution at the present time point (Luo et al., 2024; Tian & Huber, 2008). The higher the topographic similarity, the stronger the influence of the past on the present, and the higher the degree of temporal integration of past and present inputs across a given duration (i.e., timescale) (Wolff et al., 2022; Wolman et al., 2023). Topographic similarity can thus be considered a neural proxy for neural duration, which therefore reflects the timescale of an underlying neural process. We hypothesize that topographic similarity during fast tapping (short neural timescales) will correlate more strongly with task-relatedness, while topographic similarity during slow tapping (longer timescales) will be more sensitive to thought orientation. Crucially, our study goes beyond linear associations and tests whether these relationships are mediated by nonlinear mechanisms. Mounting evidence suggests that the mapping between thought and neural activity may be nonlinear—particularly for intermediate cognitive states (e.g., ambiguous task engagement) that suppress or mask linear effects (Huang et al., 2017; Northoff, Zilio, et al., 2024; Wainio-theberge et al., 2020; Wolff, de la Salle, et al., 2019). To examine this, we employed generalized additive models (GAMs) and Bayesian mediation analyses, allowing us to differentiate direct linear effects from indirect nonlinear influences.

Finally, we also investigate the neural mechanisms underlying these timescales by examining whether phase-based neural synchrony (PLV) underlies the observed patterns. Unlike traditional power-based measures, phase dynamics reflect large-scale network coordination and temporal coupling between distant brain regions (Fries, 2005; Knyazev et al., 2011). We predict that topographic similarity is fundamentally phase-based, and that the impact of thought by neural timescales is grounded in phase synchrony rather than local amplitude fluctuations.

In sum, our study aims to disentangle the temporal dynamics of two fundamental dimensions of spontaneous thought—task-relatedness and thought orientation—across cognitive, behavioral, and neural domains. By combining finger tapping, EEG-based topographic similarity, phase synchrony, and advanced nonlinear modeling, we seek to establish that these two dimensions are governed by dissociable timescales and mechanistically distinct neural processes (figure 1D).

Method

Participants

Dataset 1. Eighty-six right-handed adults participated in the study (41 female; age range = 18-30 years; mean age = 21 years, SD = 2.3 years). All had normal or corrected-to-normal vision and reported no neurological or psychiatric conditions that might affect performance. Of these, 2 were excluded as the EEG data were of insufficient quality. Ultimately, 84 participants' data were included in the final analyses. The experimental protocols were approved by the research ethics committee of the Shenzhen University and the University of Ottawa. Written informed consent was obtained from each participant prior to study participation.

Dataset 2. Thirty-five right-handed adults participated in the study (11 female; age range = 18-28 years; mean age = 22.6 years, SD = 2.4 years). All had normal or corrected-to-normal vision and reported no neurological or psychiatric conditions that might affect performance. The experimental protocols were approved by the research ethics committee of the University of Ottawa and Zhejiang University. Written informed consent was obtained from each participant prior to study participation.

Procedures

The whole procedure included two tasks: resting state, and the finger tapping task (Figure 1A). All participants were first requested to undergo the resting state recording session, during which they were asked to keep their eyes on the fixation cross on the screen, and stay relaxed for 10 minutes. There was 1 minute break between resting state and finger tapping task. During the finger tapping task, participants were presented 11 auditory tones, and they were instructed to tap following the rhythm of the tone. Then, they were instructed to tap according to the rhythm they had learnt without any cues in following 10 minutes (Figure 1A) (Amrani & Golumbic, 2021).

According to the previous literature, the spontaneous motor tempo of finger tapping is around 0.6s, meaning the ITI is around 0.6s if no external speed instruction is given to participants (Amrani & Golumbic, 2021; Rose et al., 2020). Moreover, the performance is best (with the lowest variance and highest synchronization across tapings) around ITI equals to 0.6s (Amrani & Golumbic, 2021). Accordingly, fast and slow tapping speed were set to these two tempos. For fast finger tapping, the presumed standard interval (SI) was set as 0.8s to meet the requirement of both closed to the spontaneous tempo as well as including slow EEG cycles like theta. The SI for slow finger tapping was set as 1.9s which is significantly slower than 0.8s (Amrani & Golumbic, 2021) and cannot be divided evenly by 0.8s (as to avoid any effects of harmonic frequencies) (Figure 1C). Finally, both resting state and finger tapping tasks (both fast and slow speeds) were further presented twice, once with thought probes task and once without thought probe tasks as shown in Figure 1A.

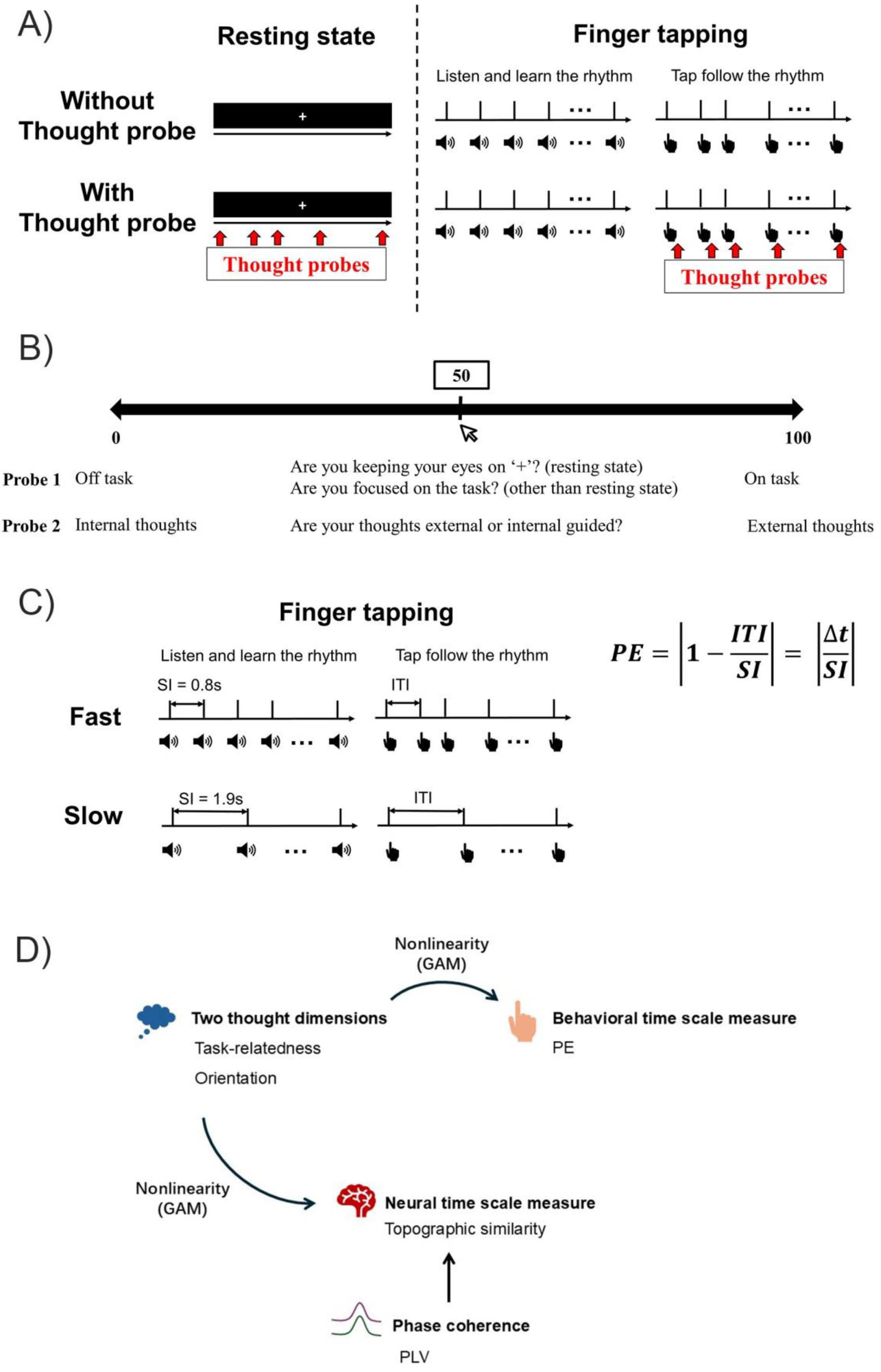

A)
Resting state
Finger tapping
Listen and learn the rhythm
Tap follow the rhythm
Without Thought probe
+
With Thought probe
+
Thought probes
Thought probes
B)
50
0
100
Probe 1 Off task
Are you keeping your eyes on '+'? (resting state)
Are you focused on the task? (other than resting state)
On task
Probe 2 Internal thoughts
Are your thoughts external or internal guided?
External thoughts
C)
Finger tapping
Listen and learn the rhythm
Tap follow the rhythm
$PE = \left|1 - \frac{ITI}{SI}\right| = \left|\frac{\Delta t}{SI}\right|$
Fast
SI = 0.8s
ITI
Slow
SI = 1.9s
ITI
D)
Nonlinearity (GAM)
Two thought dimensions
Task-relatedness
Orientation
Behavioral time scale measure
PE
Nonlinearity (GAM)
Neural time scale measure
Topographic similarity
Phase coherence
PLV

Figure 1. Schema of the experimental paradigm. A) Overall schema of experiment. The whole procedure includes two tasks: resting state and finger tapping. All participants were first requested to undergo the resting state recording, during which they were asked to keep their eyes open but fixed on the fixation on the screen and keep relaxed for 10 minutes. During the finger tapping, participants heard a tone with 11 tones first, then they were requested to tap according to the rhythm they had learnt in the following 10 minutes. Both resting state and finger tapping tasks (both fast and slow speeds) were further presented twice, once with the thought probe task and once without the thought probe task. The thought probes required participants to judge the degree in the balance of their off vs. on task and internal vs. external thoughts, respectively on a visual analogue scale ranging from 0 to 100; **B) Thought probes.** 20 thought probes were included in each task with intervals randomized from 5s to 65s, jittered in 10s intervals. Each thought probe contained two questions, one about off vs. on task thought, the other about internal vs. external thoughts; **C) Schema of finger tapping and calculation of PE.** There were two distinct speeds for the finger tapping task as indicated by the ITI: fast ITI = 0.8s, and slow ITI = 1.9s. The PE was calculated to capture the deviation between the mean of the real ITI and the presumed standard interval (SI) by using the ratio between them: PE=1-ITI/SI. **D) Schematic illustration of the analytical framework of nonlinearity and phase basis of topographic similarity. Note:** ITI: inter-tapping interval; SI: presumed standard interval; PE: precision error.

Thought probes

Thought probes are widely used in the study of mind wandering as they provide a method to detect subjective states of thought (Christoff et al., 2009; Franklin et al., 2011; Hua et al., 2022; Mills et al., 2018; Smallwood & Schooler, 2006). Thought probes are usually presented randomly during an ongoing task to detect participants' instantaneous thoughts. In this study, 20 thought probes were presented in each task (resting state and finger tapping, Figure 1A), with intervals randomized from 5s to 65s, with jittered 10s intervals. Two questions were asked each time a thought probe was presented to assess the two thought dimensions (e.g., *task relatedness, or, orientation*):

1. **Task relatedness: off vs. on task thought:**

   (In resting state): Are you keeping your eyes on '+'?

   (In task): are you focused on the task?

2. **Orientation: internal vs. external thought:**

   Is your thought externally or internally oriented?

We used different questions to assess task-relatedness during both resting state and the finger tapping task because, in the resting state, participants had no tasks to focus on, making it irrelevant to ask if their thoughts were on the ‘task’. The scores of thought probes were separated by a visual analog scale (VAS) from 0 to 100. Participants were requested to choose a score according to their state just prior to each thought probe. Higher scores indicated thoughts that are more on-task and more externally-oriented (Figure 1B).

Precision Error

The Precision error (PE) was used in this study to measure the performance of finger tapping (Amrani & Golumbic, 2020, 2021; Kliger Amrani & Zion Golumbic, 2020). PE captures the deviation between the mean of real ITI and the SI by using the ratio between them: $PE = 1 - \frac{ITI}{SI}$; The closer the PE is to zero, the more it indicates a precise replication of the given SI (Figure 1D). Prior to computing the correlation between thought VAS scores and PE, we calculated the absolute value of PE to provide a more stable metric for assessing the relationship with thought dimensions (Figure 2A).

EEG recording and preprocessing

EEG data were collected and preprocessed following the same procedure in both datasets. EEG data was collected from a 64-channel BrainAmp amplifier (Brain Products, Munich, Germany) at a sampling rate of 500 Hz. Electrode Oz was used as the online reference. The impedance for all electrodes was kept below 5 kΩ while the data was recorded. The data preprocessing was conducted using EEGLAB toolbox (Delorme & Makeig, 2004) (http://sccn.ucsd.edu/eeglab/) which is a freely available, open source MATLAB-based package for EEG data analysis. The EEG signals were re-referenced off-line to the average of all electrodes. The signals were band-pass filtered between 1 and 50 Hz using a zero-phase finite impulse response (FIR) filter implemented in EEGLAB, based on a Hamming-windowed sinc design, with the filter applied in a forward–backward manner to avoid phase distortion; the filter order was automatically determined as a function of the sampling rate and transition bandwidth. Bad channels were excluded by clean_rawdata plug-in provided in EEGLAB and default settings are used. All stationary artifacts, especially eye movements (blinks and saccades), were reduced by using Independent Component Analysis (ICA) and excluded using the MARA plug-in in EEGlab (Winkler et al., 2011, 2014).

EEG analysis

Topographic similarity

Finger tapping task. In order to evaluate temporal integration, we measured topographic similarity, i.e., whether the past tapping shares the similar topography with the present tapping (Luo et al., 2024; Tian & Huber, 2008). We first set each finger tap as the onset of interest (0ms) and segmented the EEG signals into epochs from -1200ms to 1200ms. For each time point, we averaged the signals within a 50ms window before and after and calculated the corresponding topographic map. Then, for each finger tap, we calculated the topographic similarity between the topographic maps at each time point within the -1200ms to 1200ms window and the topographic map at the corresponding time point of the previous finger tap. Topographic similarity was measured by calculating cosine similarity: $Topographic\ similarity = \frac{V_{n-1} \cdot V_n}{\|V_{n-1}\| \times \|V_n\|}$, in which V_{n-1} represents the vector of the previous tapping topography, and V_n represents the vector of the present tapping topography (Figure 3A).

If the topographic similarity is positive, it indicates that the current topography resembles the previous one, meaning there is a positive interaction between the past and present. If the topographic similarity is close to zero, it suggests that the current topography is unrelated to the previous topographies, indicating a low past-present interaction. If the topographic similarity is negative, it means the current topography has an opposite pattern to the previous one, reflecting a negative interaction between the past and present (Figure 3B).

Baseline in resting state. We also calculated the topographic similarity in the resting state as the baseline for each participant. This was done to obtain each participant's baseline, that is, the expected topographic similarity at standard intervals (fast condition = 0.8s, slow condition = 1.9s) in the absence of a task. The calculation process is similar to that used in the finger-tapping condition, with only one difference: the resting-state signal was epoched at standard intervals, with 0.8s epochs for the fast condition and 1.9s epochs for the slow condition. For each epoch, we calculated its topographic similarity with the corresponding time points of the previous epoch. Finally, all the epoch values at each timepoint were averaged to obtain the baseline topographic similarity for each participant (supplementary figure 1A & B).

Phase locking value

To investigate the relationship between topographic similarity and phase synchrony, we computed the Phase Locking Value (PLV) between consecutive tapping events, following the method introduced by Lachaux and colleagues (Lachaux et al., 1999). PLV quantifies the degree of phase synchronization between two neural signals across repeated measurements—in this case, between adjacent tapping intervals. By assessing PLV in this context, we aimed to determine whether higher topographic similarity is associated with increased inter-tap phase synchrony.

The instantaneous phase of each EEG signal was extracted using the Hilbert transform. For each pair of signals, the phase difference was computed at every time point across trials. These phase differences were converted into complex exponentials, averaged across trials, and then normalized to yield the PLV, as defined by the following formula:

$$PLV(t) = \left| \frac{1}{N} \sum_{n=1}^{N} e^{i(\phi_1(t,n) - \phi_2(t,n))} \right|$$

where $\phi_1(t,n)$ and $\phi_2(t,n)$ denote the instantaneous phase of the two signals at time t for trial n, and N is the number of trials. This yielded a time-resolved PLV curve that characterizes phase coherence across trials. To correspond with the analysis of topographic similarity, we averaged the PLV values across all electrode sites after computing them at each site, resulting in a scalp-wide PLV measure.

Phase shuffling

To further test whether topographic similarity is fundamentally phase-based, we performed phase shuffling on the EEG time series (Lechner & Northoff, 2023). This method generates surrogate signals that preserve the spectral power distribution while disrupting the temporal structure (Theiler et al., 1992). Each time series was first transformed into the frequency domain via fast Fourier transform (FFT). The amplitude spectrum was preserved, while the phase spectrum was randomly shuffled under the constraint of Hermitian symmetry, ensuring that the inverse transform yields a real-valued signal. Specifically, random phase values were drawn uniformly from $[-\pi, \pi]$, for the positive frequencies, and the corresponding negative frequency components were assigned their complex conjugates. The inverse FFT was then applied to reconstruct a time-domain surrogate signal that retains the original power spectrum but lacks the original phase relationships. This approach provides a stringent control for testing the temporal specificity of phase-based neural metrics.

After phase shuffling, PLV and topographic similarity were recalculated. The correlations between PLV, topographic similarity, and both PE and thought ratings were then recomputed using the same procedures as in the non-shuffled condition. To assess the similarity between topographic similarity and thought following phase shuffling, we not only shuffled the EEG signals from both the fast and slow tapping conditions, but also shuffled the EEG signals from the resting state. We then computed the difference between tapping and resting states and examined its correlation with thought. This approach ensured maximal consistency with the original (non-shuffled) analysis pipeline.

Event-related spectral perturbation

To complement our primary focus on phase-based neural dynamics, we additionally examined event-related spectral perturbation (ERSP) as a canonical amplitude-based EEG measure. ERSP has been widely used to characterize task-evoked changes in oscillatory power and is commonly interpreted as reflecting local neural activation and resource allocation during cognitive processing. (Bocharov et al., 2019; Wolff, Gomez-Pilar, et al., 2019). By including ERSP analyses, we aimed to determine whether the relationships between thought dimensions, behavior, and neural timescales observed in phase-based measures could also be captured by traditional power-based indices, or whether they are specific to phase-dependent temporal coordination. This comparison allows us to delineate the functional contributions of amplitude- versus phase-based neural dynamics in shaping ongoing thought and behavior.

Following previous literature, we selected three standard electrode sites—Fz, Cz, and Pz—for analysis (Barron et al., 2011; Polich, 2003). Baseline correction was performed using the −800 to −100 ms window prior to each tapping event. Consistent with the topographic similarity analysis, each epoch was time-locked to the tapping onset (0 ms) and spanned from −800 ms to 800 ms. To assess condition differences, we applied a cluster-based permutation test to the ERSP data across the −800 to 800 ms time window and the 1–40 Hz frequency range (1000 permutations, cluster-forming threshold $|t| > 2.0$). Additionally, we identified time–frequency clusters whose power values were significantly correlated with precision error (PE) and subjective thought ratings (VAS scores) (1000 permutations, cluster-forming threshold $|r| > 0.2$).

Statistical analysis

Trial-based correlation

To capture the moment-to-moment variability of thought states and their immediate behavioral and neural correlates, we conducted a trial-based analysis rather than a subject-based analysis to examine the relationship between thought, PE, and topographic similarity. Subject-level analyses primarily reflect stable individual differences (i.e., trait-like properties), whereas our primary interest lay in state-dependent fluctuations of thought and their trial-by-trial coupling with behavioral precision and neural dynamics. A trial-based framework therefore provides a more appropriate resolution for examining how transient thought states affect ongoing behavior and neural activity. Specifically, we aggregated trial data from all participants and assessed the correlation between the trial-based thought VAS scores and the respective trial-based indices of both behavioral (PE) and neural (topographic similarity) measures. Such a single trial-based approach is commonly used in other domains (Polanco-Martinez et al., 2019; Taheri-Araghi et al., 2015) which we extend and apply here to the single thought probes: our focus was mainly on neural (topographic similarity) and behavioral (PE) changes related to states of the thoughts themselves rather than to the subjects' trait features exhibiting those thoughts. This was further reflected in our usage of a continuous rating of thoughts with a continuum between the extremes of internal/external and on/off task: this allowed for a more fine-grained assessment of the single thought probes than the usual binary (on vs off, internal vs external) choice. This is also reflected in the distributions of the thought VAS scores, which did not exhibit a bimodal pattern but rather a continuum within and across participants (Supplementary Figure 2). Unlike the binary distribution often assumed in previous studies using thought probes (Hua et al., 2022; Smallwood & Schooler, 2006), our findings highlight a continuous nature of thought states thus confirming the usage of a continuous VAS rather than the binary choice. Our primary focus was thus on the overall patterns of variation between the different single trial thought probes across subjects, rather than inter-subject differences (Frömer et al., 2018; Hua et al., 2022).

After pooling the single trial thought probes across participants, we averaged the trial values corresponding to each segment of the VAS score (e.g., 0–1, 1–2, 2–3, etc.) for several reasons: 1. to mitigate the risk of overly significant correlations caused by the large number of single trials; 2. to reduce noise stemming from the inherent subjective nature and imprecision of the participants' VAS ratings, as segment averaging allows for smoothing out the variability related to inter-individual differences; 3. to equalize the weighting of each VAS score segment and prevent biases due to uneven distribution of trial counts across segments (Polanco-Martinez et al., 2019; Taheri-Araghi et al., 2015). We further selected values with z-scores between -3 and 3 for Pearson correlation analysis, minimizing the influence of outliers while ensuring the data remained representative and sensitive to overall trends. Finally, we conducted analogous single-based analyses for both behavioral (PE) and neural (topographic similarity) measures to allow for their correlation with the single trial thought probes.

Calculation of the thought's impact on topographic similarity.

The resting state serves as a baseline for subsequent task-related activities(Huang et al., 2017; Northoff et al., 2010, 2022). Consequently, internal cognition associated with the resting state (Buckner & DiNicola, 2019; Menon, 2023) may carry over to the subsequent task states, potential confounding task-related measures. To control for such carry-over effects, we calculated topographic similarity in the resting state with the same time intervals (0.8s or 1.9s) used in the two task states respectively (fast and slow), a method analogous to the 'pseudo-trial' approach described by Huang and colleagues (Huang et al., 2017); these resting state results were then subtracted from the task states measures, isolating the task-specific effects of topographic similarity. This approach allowed us to differentiate between task-related cognitive processes and those carried over from the resting state, while also accounting for the interaction of timescales (slow, fast) with task-specific thoughts.

This allowed us to calculate the correlation between the task-rest difference of topographic similarity and the thought dimensions (task-relatedness and thought orientation) in a trial-based way (as described above). The absolute value of the correlation coefficient from these correlations served as the measure of thought's impact on topographic similarity (supplementary figure 1B).

To verify that the impact of thought on task-related topographic similarity truly reflects the influence of thought, rather than the differences caused by the given tapping intervals themselves, we conducted partial correlation in which the difference between ITI and SI was included as a covariate to control for the effects of the SI given in the slow and fast tapping tasks. If the results of this partial correlation, after accounting for the covariate, remain consistent with the original findings of the thoughts' impact on topographic similarity, it would confirm that the observed effects are due to the thoughts themselves rather than merely being related to the given tapping intervals during the tapping behavior.

Comparing thought impact on topographic similarity between thought dimensions

We performed 1000 bootstrap resamples on segmented trials. In each resample, we calculated the thought impact on topographic similarity for both thought dimensions and then subtracted the one for the thought orientation dimension from the one for the task-relatedness dimension. Finally, we used a one-sample t-test to compare the distribution of the 1000 resampled differences to 0. If the result was significantly greater than 0, it indicated that task-relatedness has a stronger impact on topographic similarity, meaning that the task-relatedness dimension contributed more to the topographic similarity. Conversely, if the result was significantly less than 0, it indicated that thought orientation has a stronger impact, meaning that the thought orientation dimension contributed more to the topographic similarity (Figure 4C).

We also performed 1000 times permutation test on the difference of the impacts of different thought dimensions on segmented trials following the procedure proposed by Maris and colleagues (Maris & Oostenveld, 2007). To do so, we calculated the difference of thought impact on topographic similarity following the same procedure as above as the 'observed difference', then we applied 1000 times of permutation, and got the distribution of 'permutation difference'**.** if the observed difference is significantly larger than the permutation difference, that is, the difference between the impact of task relatedness and orientation is significantly larger than the randomized level, i.e., 0, we can infer that the **task relatedness's** impact on topographic similarity is significantly higher than **orientation's impact**; on the contrary, if the observed difference is significant lower than the permutation difference, orientation's impact is significantly higher than task relatedness's impact.

Linear Mixed Models and Generalized Additive Models

To further control for inter-individual variability and to deepen our interpretation of the observed double dissociation effects, we conducted follow-up analyses using linear mixed-effects models (LMMs). As a preprocessing step, trials with values exceeding three standard deviations from the mean were excluded to minimize the influence of extreme outliers. The remaining data were then binned within each participant based on their thought dimension scores (task-relatedness and orientation) to reduce intra-subject noise and facilitate smoother trend estimation.

Subsequently, LMMs were constructed to evaluate the relationship between the thought dimensions and either behavioral precision error (PE) or the neural measure of topographic similarity. To assess potential nonlinear associations between thought scores and these outcome variables, we additionally employed Generalized Additive Models (GAMs). Because nonlinear relationships can obscure or distort linear effects, isolating the linear component requires explicitly accounting for nonlinear trends. Extracting residuals from GAMs provides a principled way to remove nonlinear structure from the data, allowing subsequent LMMs to test whether any remaining linear association persists after nonlinear effects are controlled. Specifically, GAMs were fitted to model the nonlinear trends between PE or topographic similarity and the continuous visual analog scale (VAS) ratings for each thought dimension. To isolate the linear component of these relationships, we extracted the residuals from the GAMs and re-entered them into LMMs.

Moreover, to formally test whether the degree of nonlinearity between thought dimensions and outcome measures on behavioral level (PE) differed across fast and slow tapping conditions, we implemented interaction GAMs. For each predictor (task-relatedness and orientation), data from both tapping conditions were merged and labeled accordingly. We then fitted interaction GAMs using the mgcv package in R (Wood, 2017), incorporating condition-specific smooth terms:

Bayesian Nonlinear Mediation Analysis Using Smooth Functions of Thought Variables

Building on the previously identified nonlinear relationships between thought dimensions and both PE and topographic similarity, we next investigated whether such nonlinearity mediate the effects of thought on behavioral and neural outcomes. Traditional mediation frameworks typically assume linear relationships between the predictor (X), mediator (M), and outcome (Y). However, prior research suggests that neural responses often exhibit nonlinear associations with psychological constructs such as thought (Huang et al., 2017; Northoff, Zilio, et al., 2024), which may be poorly captured by linear models. To address this limitation, we employed a Bayesian mediation approach designed to incorporate nonlinear components of thought-related predictors.

In these models, thought VAS scores were entered as predictors with smooth terms, and behavioral (PE) or neural (topographic similarity) measures served as outcomes. Generalized additive models (GAM) were used to flexibly capture nonlinear associations at the trial level. Subject-level dependence was addressed at subsequent modeling stages, including Bayesian mediation analyses, to account for repeated measurements.

To examine mechanistic pathways, we conducted a Bayesian nonlinear mediation analysis, in which the nonlinear component estimated by the GAM (i.e., the smooth function of thought) was treated as the mediating variable. This approach differs fundamentally from traditional linear mediation models, as the mediator represents a nonlinear transformation of the predictor rather than a single linear coefficient.

The Bayesian framework was chosen because it allows direct estimation of uncertainty in the nonlinear mediator and propagates this uncertainty into the posterior distribution of the indirect effect. Mediation effects were therefore evaluated based on the posterior distribution of the nonlinear indirect pathway, rather than relying on normality or linearity assumptions.

This modeling strategy enables direct testing of whether nonlinear variations in neural or behavioral timescales mediate the relationship between thought dimensions, while preserving the graded and dynamic nature of the underlying processes.

Two-Step Modeling Strategy

To capture potential nonlinear mediation effects, we adopted a two-step analytical strategy:

Nonlinear Trend Estimation via GAM: We first used Generalized Additive Models (GAMs) to estimate the smooth, nonlinear relationship between the outcome variable (PE or topographic similarity) and the thought dimension of interest (e.g., task-relatedness or orientation). The smooth term, s(thought) extracted from the GAM reflects the nonlinear transformation of the predictor and serves as a proxy for its latent effect.

Bayesian Mediation Using Smooth-Term as Mediator:

The fitted values of s(thought) were then used as the mediator (M) in a Bayesian mediation model, capturing how the nonlinear component of the thought variable mediates its influence on PE or topographic similarity. In this framework, the raw thought VAS score was treated as the independent variable (X), and PE or topographic similarity served as the dependent variable (Y).

Model Specification and Estimation

We specified a pair of linked regression models within a fully Bayesian framework:

Mediator Model (Path a): $\boldsymbol{M} = \alpha_{\boldsymbol{m}} + \beta_{\boldsymbol{m}} \cdot \boldsymbol{X} + \varepsilon_{\boldsymbol{m}}$

Outcome Model (Paths b and c′): $Y = \alpha_y + \beta_y \cdot X + \beta_M \cdot M + \varepsilon_y$

Indirect Effect: Indirect $= \beta_m \cdot \beta_M$

Total Effect: Total $=$ Indirect $+ \beta_{\boldsymbol{y}}$

Model parameters were estimated using Markov Chain Monte Carlo (MCMC) sampling, enabling us to obtain posterior distributions for each parameter. This allowed for robust inference based on mean posterior estimates, 90% Credible Intervals (CIs), and posterior probabilities of direction, thereby quantifying both the magnitude and credibility of indirect and direct pathways. A parameter was considered significant if its 90% CI did not include zero, indicating a consistent direction of effect across the posterior distribution.

Results

Cognitive level: Thought orientation and task-relatedness dimensions are dissociable

To compare the two thought dimensions at the cognitive level, we first compared their two visual analogue scales (VAS) ratings with each other during all conditions (resting state and the two finger tapping tasks). The results show that the participants' scores for thought orientation are significantly lower than those for task-relatedness in all three conditions (resting state: t(83) = 14.30, $p < 0.001$; fast finger tapping: t(83) = 8.56, $p < 0.001$; slow finger tapping: t(83) = 8.40, $p < 0.001$, Figure 2B, Supplementary Figure 4A). Hence, the balance of thought orientation is rated subjectively different than that of task-relatedness. At the subjective level, if participants considered these two dimensions to be two constructs that assess the same underlying thought dimension, we would expect the rating to be similar. Specifically, the VAS scores task-relatedness were around 70 while the scores of thought orientation were around 40-50, consistently, in the three conditions (resting state: off-on task: mean = 72.75, std = 16.14; internal-external: mean = 39.32, std = 15.75; fast tapping: off-on task: mean = 66.67, std = 18.04; internal-external: mean = 46.10, std = 19.68; slow tapping: off-on task: mean = 68.95, std = 17.82; internal-external: mean = 46.16, std = 21.18). This pattern of scores indicates that the balance between on vs. off tasks thought leans more toward the on-task end of the spectrum, whereas the internal vs. external balance is more intermediate (i.e., neither one, nor the other).

Next, we raised the question of whether the ratings for the two thought dimensions were correlated to each other. The results showed a significant correlation between the task-relatedness and thoughts orientation dimension scores during the fast finger tapping task (r(82) = 0.32, p = 0.003; Supplementary Figure 3), whereas no significant correlations were obtained in both resting state and slow finger tapping (resting state: r(82) = 0.10, p = 0.377; slow finger tapping: r(82) = 0.20, p = 0.075; Supplementary Figure 3). These data suggest that the relation between the two thoughts dimensions differs across the three conditions with only the fast finger tapping suggesting that they are related to one another, while they remain independent in both rest and slow finger tapping.

Are task-relatedness and thoughts orientation different thought dimensions rather than just different metrics of the same underlying continuum? If they are just different degrees on the same continuum, one would expect high ratings for internal thought to correlate with high ratings for off-task thoughts, while high ratings for external thought should align with high ratings for on-task thoughts. To test for this, we performed a median split on each participant's thought probes based on their VAS scores. The top 10 trials with the highest scores were classified as on-task or external thought trials, while the lowest 10 trials were classified as off-task and internal thought trials. We then calculated, for each participant, the number of trials that fell into the following four combinations: 1) on-task and internal, 2) off-task and internal, 3) on-task and external, and, 4) off-task and external. Since the counts of the four combinations are not continuous variables, we used the non-parametric Friedman test to determine whether there are significant differences among the counts of the four combinations. This approach revealed no significant differences in these four combinations during the resting state (Friedman statistic = 0.00, p > 0.999; Supplementary Figure 4B). While significant differences were found among the four groups during both fast and slow finger tapping (fast: Friedman statistic = 13.34, p = 0.004; slow: Friedman statistic = 17.75, p = 0.001; Figure 2C), multiple comparison tests showed no significant pairwise differences between the four categories in either fast or slow finger tapping (all p > 0.05; Figure 2C, see Supplementary Table 1 and Supplementary Table 2 for detailed results).

Together, these results suggest that while there is some degree of correlation between task-relatedness and thought orientation, there is no strict correspondence between on-task and external thoughts nor between off-task and internal thoughts. This supports the assumption that task-relatedness and thought orientation are indeed distinct dimensions of thought, rather than being different degrees or scales of one and the same dimension. In summary, all three findings, VAS rating degrees, correlation analysis, and association of thoughts, suggest that, based on their subjective assessment, task-relatedness and thought orientation are distinct dimensions rather than variations of one and the same underlying dimension.

Behavioral level: Thoughts orientation relates to the longer timescale of slow finger tapping while task-relatedness relates to the shorter timescale of fast finger tapping

We next investigated the timescales of orientation and task-relatedness. We first observed that PE was not significantly different from 0 in both fast and slow tapping, as indicated by one-sample t-tests (fast: mean (95% CI) = -0.02 (-0.08, 0.04), SD = 0.26, SEM = 0.03, t(83) = 0.71, $p_{fdr(1)} =$ 1.000; slow: mean (95% CI) = 0.04 (-0.01, 0.08), SD = 0.22, SEM = 0.02, t(83) = 1.46, $p_{fdr(1)} =$ 1.000). These results indicate that the deviation of the participants' actual tapping intervals from the SI during the experiment was minimal, with no systematic bias observed in either slow or fast finger tapping conditions. We also observed that the PE is not significantly different between fast and slow finger tapping (t(83) = 1.78, p = 0.079; Supplementary Figure 5). Moreover, the absolute value of PE is also not significantly different between fast and slow finger tapping (t(83) = 0.12, p = 0.904; Supplementary Figure 5). These results suggest that no significant change of PE occurred due to the duration of the tapping intervals, which are longer in slow finger tapping, and shorter in fast finger tapping.

Next, we investigated the interaction of PE with our two thought dimensions during both slow and fast finger tapping. The results show that the PE during slow finger tapping is only related with internal-external thought but not with off-on task thought (task relatedness: r(90) = 0.01, $p_{fdr(1)} =$ 1.000; orientation: r(93) = -0.66, $p_{fdr(1)} < 0.001$; Figure 2D). While fast finger tapping PE only relates with task-relatedness thought but not with thought orientation (task-relatedness: r(95) = -0.41, $p_{fdr(1)} < 0.001$; orientation: r(98) = -0.19, $p_{fdr(1)} =$ 0.072; Figure 2D). Together, these results show double dissociation between timescales (slow and fast finger tapping) and thought dimensions (task-relatedness, thought orientation): thought orientation is associated with longer timescales of the slow finger tapping whereas task-relatedness relates to shorter timescale of the fast finger tapping.

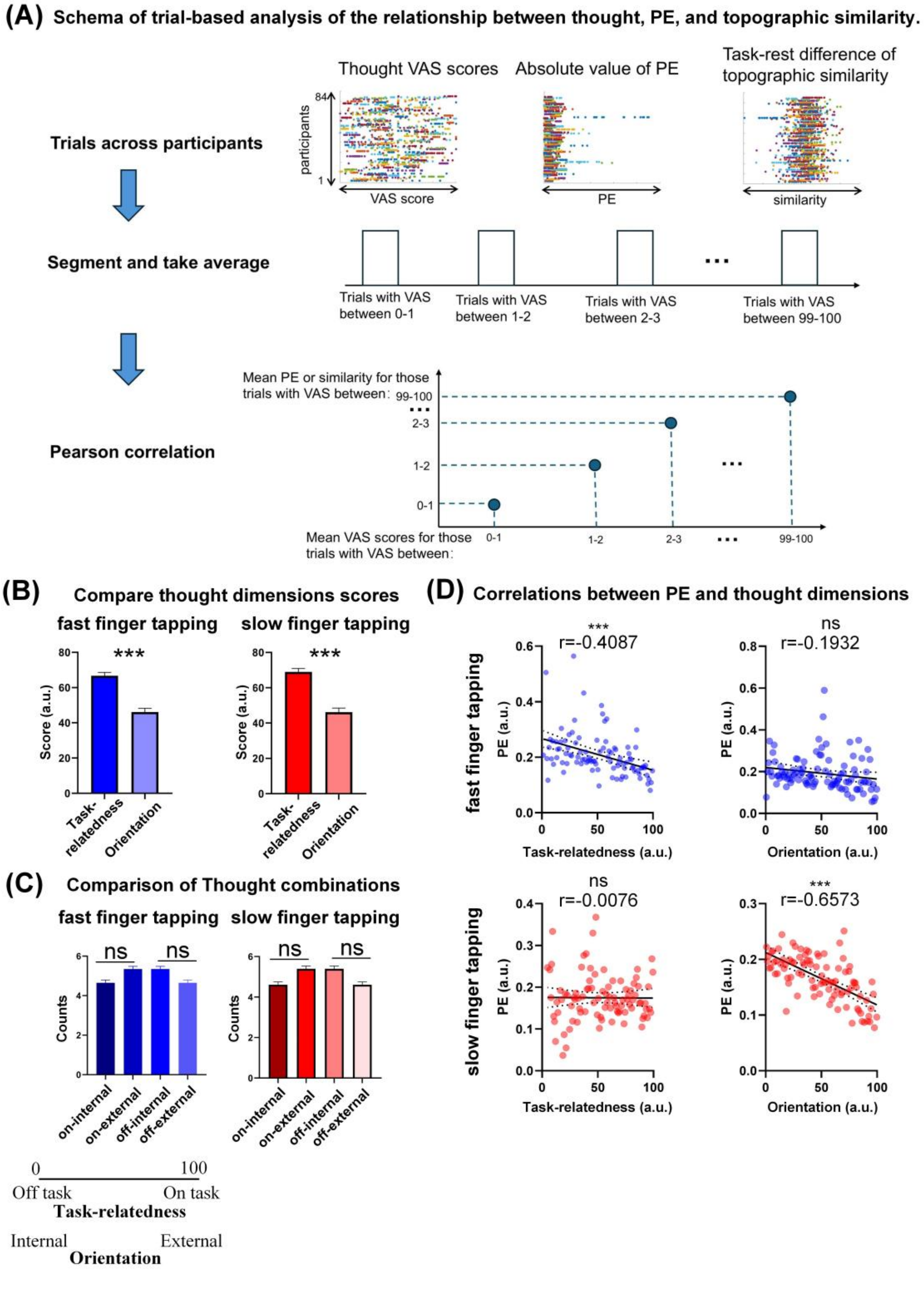


Figure 2. Behavioral results. (A) Schema of trial-based analysis of the relationship between thought, PE, and topographic similarity. Data from all participants were aggregated to assess correlations between thought VAS scores and timescale indices at behavioral (PE) and neural (topographic similarity) levels. The analysis was motivated by our focus on the single trial differences between the thought probes themselves as distinct from the inter-subject differences

related to the different thoughts which is also reflected in and measured by the continuous assessment in our VAS with a grading between the extremes of internal-external and on-off (as distinct from the standardly used binary assessment of internal-external and on-off thoughts). Trial values were averaged within VAS score segments (e.g., 0–1, 1–2, etc.) to mitigate noise, balance segment weighting, and reduce over-significance. Pearson correlation analysis was performed on z-scored values (-3 to 3), and absolute PE values were used to provide a stable metric for thought dimensions. **(B)Comparison between task relatedness and orientation VAS scores.** Task relatedness and orientation VAS scores in fast and slow finger tapping are compared by paired T-test. The results show that in both speeds, the participants' scores for thought orientation (internal-external dimension) are significantly lower than for task-relatedness (off-on task dimension). **(C) Comparison of thought combinations.** The counts of trials with on-task and internal, off-task and internal, on-task and external, and off-task and external for each participant were compared by Friedman test. Although significant differences were found among the four groups during both fast and slow finger tapping, multiple comparison tests showed no significant pairwise differences between the four categories in either fast or slow finger tapping. (**D) Correlation between PE and thought dimensions.** The interaction of orientation and task relatedness with PE during both slow and fast self-paced finger tapping were tested by applying binned correlation. Each dot represents one VAS score on Y axis and the averaged PE value across all trials with that VAS score on X axis. Results show that slow speed finger tapping is only related with internal-external thought but not with off-on task thought. While fast finger tapping PE is only related with off-on task thought but not with internal-external thought. **Note:** Error bars represent SEM; VAS: visual analog scale; PE: precision error; **: p < 0.01; ***: p < 0.001; ***: p < 0.001; ns: none significance.

Behavioral level: Task-relatedness impacts PE in a nonlinear manner while orientation impacts PE in linear way

To control for individual variability, we first applied LMMs and observed a marginal negative association between task-relatedness and PE in the fast tapping condition (Beta = -0.0006, t = -1.87, 95% CI [-0.001, 0.000]), whereas orientation showed no effect (Beta = 0000, t = 0.04, 95% CI [-0.0005, 0.0005]). To test for potential nonlinear structure, we fitted GAMs and found that task-relatedness exhibited mild nonlinearity (edf = 2.23, p = 0.10), which accounted for its original effect; after regressing out this component, the LMM residuals showed no significant relationship (Beta = 0.0001, t = 0.25, 95% CI [-0.0005, 0.0007]). Conversely, orientation revealed a strong linear association after adjustment (Beta = 0.0010, t = 3.83, 95% CI [0.0005, 0.0015]), with GAM confirming a strictly linear structure (edf = 1.00, p = 0.0002). In the slow tapping condition, task-relatedness again showed a significant negative effect in the initial LMM (Beta = -0.0010, t = -2.85, 95% CI [-0.0017, -0.0003]), but was later explained by pronounced nonlinearity in the GAM model (edf = 5.03, p = 0.0009); controlling for this, the effect was eliminated (Beta = 0.0000, t = -0.02, 95% CI [-0.0007, 0.0007]). Orientation remained a robust linear predictor (edf = 1.04, p < 0.0001), demonstrating consistency across timescales. Full model details are provided in supplementary table

3, including effect sizes, standard errors (SE), t-values, and 95% CI for the LMMs, as well as estimated degrees of freedom (edf), F-values, and p-values for the GAMs.

To formally assess whether nonlinear processes mediated these effects, we conducted Bayesian mediation analyses. Task-relatedness showed significant indirect effects in both fast and slow conditions (fast: mean = -0.11, 90% CI [-0.20, -0.04]; slow: mean = -0.12, 90% CI [-0.16, -0.08]), while direct effects were non-significant. This indicates a suppression mechanism where the nonlinear mediator reversed the direct trend. Orientation, by contrast, showed no significant indirect or direct effects but a consistently significant total effect (e.g., fast: mean = -0.18, 90% CI [-0.25, -0.10]), supporting a direct, linear contribution.

Finally, to compare the magnitude of nonlinear effect across temporal contexts, we applied an interaction GAM. Task-relatedness showed significantly stronger nonlinearity in the slow vs. fast tapping condition (F = 2.45, p = 0.027), whereas the linear structure for orientation was stable across conditions (F = 0.64, p = 0.493).

Taken together, these results indicate that the nonlinear relationship between task-relatedness and PE suppresses its overall effect, with this suppression being more pronounced under the slow tapping condition. In contrast, orientation contributes to PE in a consistent and robust linear fashion, and this linear effect may become more detectable when the influence of task-relatedness is masked by nonlinearity. Full model details and diagnostics are presented in Supplementary Tables 4–6.

Neural level: Topographic similarity correlates with the PE during both slow and fast finger tapping

We so far showed differences in thought orientation (internal-external dimension) and task-relatedness (off-on task dimension) in both their cognitive evaluation and their interactions with short vs. long behavioral timescales. Next, we investigated whether these timescale / duration differences on the behavioral level also manifested at the neural level. To operationalize duration on the neural level, we used the topographic similarity to measure the degree of similarities in the topographic distribution of the EEG signal of the present time points with the ones in the past (Huber et al., 2008; Luo et al., 2024; Tian & Huber, 2008). Given that task-relatedness and thought orientation were differentially related with the short vs. long timescales for finger tapping at the behavioral level, we expected to observe analogous differences in their underlying neural duration, in terms of topographic similarity.

The results show that the topographic similarity during fast finger tapping was significantly higher than in slow finger tapping (t(83) = 21.01, p < 0.001, Figure 3C); This suggests that the influence of preceding finger taps is stronger during fast tapping, where time intervals are shorter, compared to slow tapping with longer intervals. This suggests that the longer timescale of slower finger tapping and the shorter timescale of faster finger tapping are also manifest at the neural level in a corresponding manner.

Next, we asked whether these distinct neural durations, measured by topographic similarity during fast and slow finger tapping were related to the PE. For that purpose, we examined the correlation between the peak values of topographic similarity and the PE in both slow and fast tapping conditions by Pearson correlation. The results indicated a significant correlation between PE and topographic similarity at both speeds (fast: $r(80) = 0.44$, $p_{fdr\,(1)}$-< 0.001; slow: $r(80) = 0.89$, $p_{fdr(1)} < 0.001$, Figure 3D). These findings demonstrate clear relationship between PE at the behavioral level and the topographic similarity at the neural level.

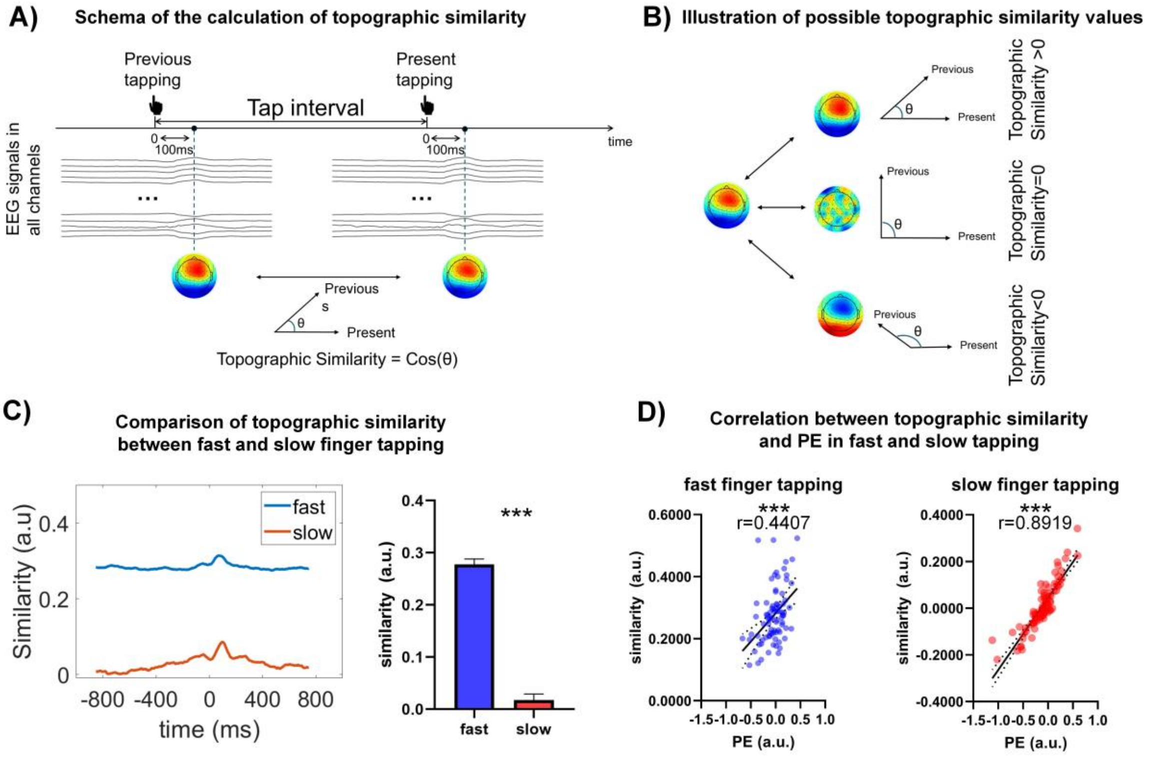


Figure 3. Topographic similarity. A) schema of the calculation of topographic similarity. For each finger tap event, we calculated the topographic similarity between the topographic maps at each time point within the -1200ms to 1200ms window and the topographic map at the corresponding time point of the previous finger tap event. Topographic similarity was measured by calculating cosine similarity: Topographic similarity $= \frac{V_{n-1} \cdot V_n}{\|V_{n-1}\| \times \|V_n\|}$, in which V_{n-1} represents the vector of the previous tapping topography, and V_n represents the vector of the present tapping topography. **B) Illustration of possible topographic similarity values.** If the topographic similarity is positive, it indicates a positive interaction between the past and present. If the topographic

similarity is close to zero, it suggests a low past-present interaction. If the topographic similarity is negative, it means the current topography has an opposite pattern to the previous one, reflecting a negative interaction between the past and present. **C) comparison of topographic similarity between fast and slow finger tapping.** The averaged values of topographic similarity between 0ms-300ms window were used as the peak value. The peak values within each participant were averaged and were compared between fast and slow finger tapping conditions using paired sample T-test. The results showed that the topographic similarity in fast finger tapping was significantly higher than in slow finger tapping, suggesting that the impact of previous tapping on the present tapping decreases with longer intervals. **D) Correlation between topographic similarity and PE in fast and slow tapping.** The correlation between the peak values of topographic similarity and the PE in both slow and fast tapping conditions were examined by Pearson correlation. The results indicated a significant correlation between PE and topographic similarity at both speeds, suggesting that topographic similarity is related to PE regardless of the interval length. **Note:** Error bars represent SEM; PE: precision error; ***: p<0.001.

Finally, to ensure that the relationship between topographic similarity and PE was truly driven by the task itself—namely, the finger tapping and its time intervals—we also calculated the difference in topographic similarity between task and resting states and then examined the correlation between the rest-task difference and the PE of the finger tapping. As in the above results, this again revealed significant correlation of the task-rest differences of the topographic similarity with the PE in both slow and fast finger tapping (fast: $r(80) = 0.41$, $p_{fdr(1)} = 0.001$; slow: $r(80) = 0.83$, $p_{fdr(1)} < 0.001$, Supplementary Figure 1C).

Neural level: Task-relatedness and thought orientation relate differently to topographic similarity during fast and slow finger tapping

Are the different timescales at the neural level during slow and fast finger tapping, as measured by the topographic similarity, related to our two thought dimensions, namely task-relatedness and thought orientation? To address this, we calculated the task-rest difference of topographic similarity by subtracting the resting state topographic similarity (used as a baseline) from the corresponding similarity at each timescale during the finger-tapping task (0.8s in resting state corresponds to fast tapping, 1.9s in resting state corresponds to slow tapping). This approach isolated the true effect of thoughts on topographic similarity during the finger tapping task itself by removing resting-state influences that are carried over to the task state. Following the approach used in the behavioral analysis, we calculated the single-trial based correlation between the task-rest difference of topographic similarity and the thought dimensions. The results show that for fast finger tapping, task-rest difference of topographic similarity is correlated with task-relatedness ($r(95) = 0.43$, $p_{fdr(3)} < 0.001$) but not thought orientation ($r(98) = 0.13$, $p_{fdr(3)} = 1.000$, Figure 4A). Whereas for slow finger tapping, the task-rest difference of topographic similarity correlates only with thought orientation ($r(91) = -0.36$, $p_{fdr(3)} < 0.001$) but not with task-relatedness ($r(91) = -0.04$, $p_{fdr(3)} = 1.000$). These results reveal a double dissociation between the neural basis of the task-relatedness dimension and the thought orientation dimension with respect to fast vs. slow finger tapping.

As another control, we tested whether topographic similarity across SI during the resting state were related to thought. The results show that in both fast and slow conditions (with SI = 0.8s and SI = 1.9s, respectively), resting-state topographic similarity was not correlated with either thought dimension. Specifically, for fast SI: task-relatedness ($r(87) = 0.03$, $p_{fdr(3)} = 1.000$) and orientation ($r(98) = -0.13$, $p_{fdr(3)} = 1.000$); and for slow SI: task-relatedness ($r(92) = 0.24$, $p_{fdr(3)} = 1.000$) and orientation ($r(98) = 0.07$, $p_{fdr(3)} = 1.000$) showed no significant correlations (see Supplementary Figure 6). These results suggest that the interaction between thought and PE is specifically related to the actual tapping and the participants's PE rather than the SI themselves.

In a second step, we performed 1000 bootstrap resamples across all trials for all participants, calculating the correlation between each thought dimension and task-rest difference of topographic similarity and then computed the difference between the task-relatedness and the thought orientation dimensions. A one-sample T-test was used to compare the distribution of these 1000 differences to 0, indicating whether task or thought orientation contributed more to the topographic similarity (Figure 4B). These results demonstrate a double dissociation between the two thought dimensions. Specifically, during fast finger tapping, the impact of task-relatedness on topographic similarity was significantly greater than thought orientation (mean = 0.29, SD = 0.12, SEM = 0.004, $t(98) = 74.47$, $p < 0.001$; Figure 4C). Conversely, during slow finger tapping, the impact of thought orientation on topographic similarity was significantly greater than that for task-relatedness (mean = -0.271, SD = 0.13, SEM = 0.004, $t(98) = 65.20$, $p < 0.001$; Figure 4C). Furthermore, the permutation results also show the same double dissociation between task relatedness and orientation (fast tapping: observed difference = 0.304, permutation difference: mean (95%CI) = 0.002 (-0.176, 0.177), $p_{fdr} < 0.001$; slow tapping: observed difference = -0.319, permutation difference: mean (95%CI) =0.003 (-0.164, 0.178), $p_{fdr}<0.001$; Figure 4D).

To confirm that the observed double dissociation of thought dimension on topographic similarity was due to the influence of the thoughts themselves, rather than differences in motor tapping behavior, we included the difference between ITI and SI as a covariate and conduct partial correlations. The results showed that even after controlling for the covariate, the effect of task-relatedness thought during fast finger tapping remained significant ($r(94) = 0.43$, $p <0.001$) while thought orientation was not ($r(94) = 0.14$, $p = 0.159$). Conversely, for slow finger tapping, task-relatedness $r(93) = -0.02$, $p = 0.883$) was not significant, while thought orientation remained significant ($r(93) = -0.36$, $p < 0.001$).

Together these results indicate that, after controlling the impact from the tapping interval in fast finger tapping, task-relatedness significantly influences the topographic similarity, while thought orientation thought does not. In contrast, the situation is reversed during slow finger tapping, whereby thought orientation significantly influences topographic similarity whereas task-relatedness does not. Since we also included finger tapping behavioral performance variables as covariates, these correlations strongly suggest that the double dissociation of task-relatedness and thought orientation for the topographic similarity at long vs. short timescales is driven by the thoughts themselves and their different timescales, rather than by the tapping behavior *per se*.

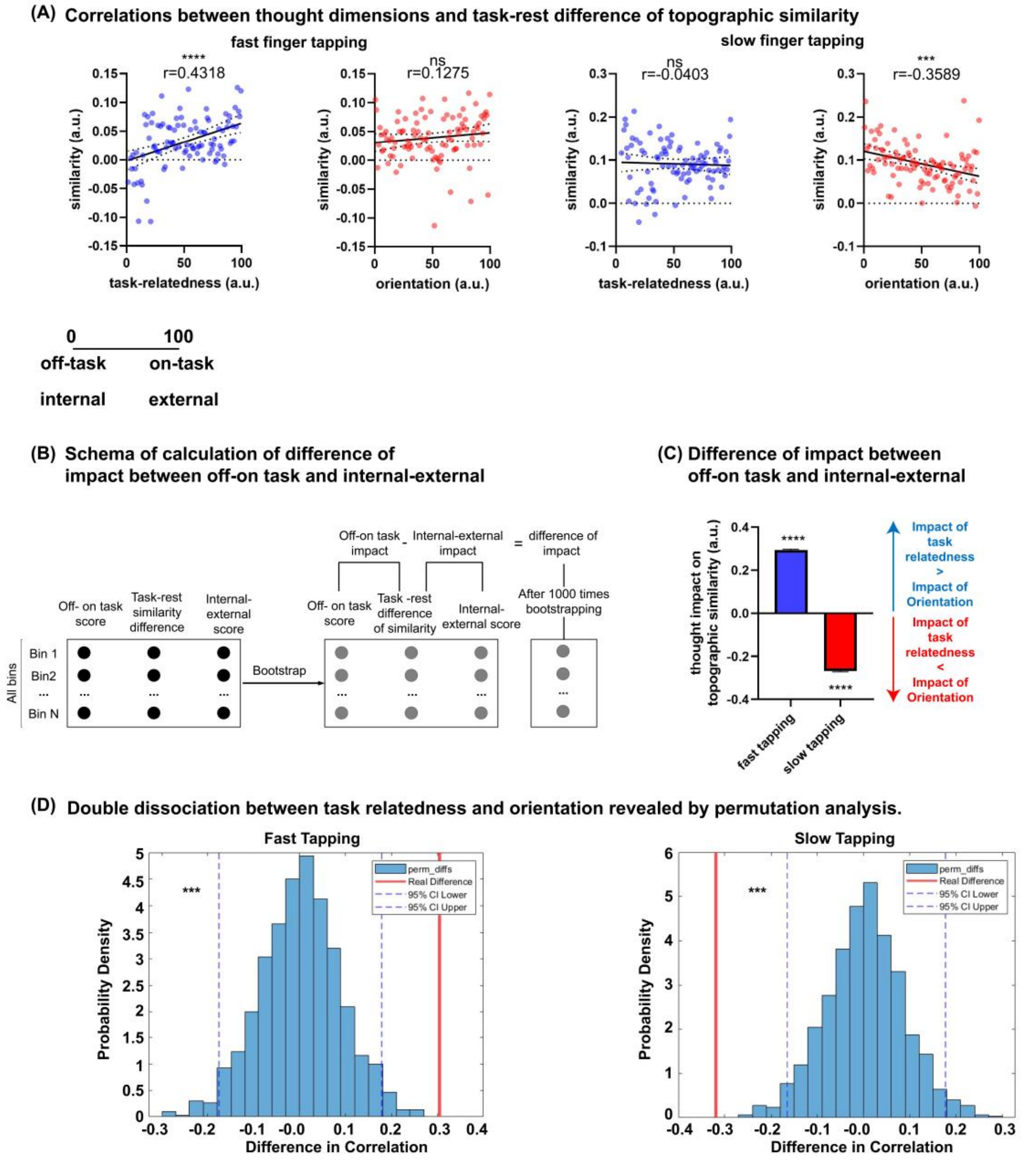


Figure 4. Thought dimension impact on topographic similarity. (A) Correlations between thought dimensions and task-rest difference of topographic similarity. The results show that for fast finger tapping, task-rest difference of topographic similarity is correlated with task-relatedness but not thought orientation. Whereas for slow finger tapping, task-rest difference of topographic similarity correlates only with thought orientation but not with task-relatedness. These results reveal

a double dissociation between the neural basis of the task-relatedness dimension and the thought orientation dimension with respect to fast vs. slow finger tapping. **(B) Schema of calculation of difference of impact between task-relatedness and thought orientation.** We performed 1000 bootstrap resamples for the segmented data, calculating the impact of thought on topographic similarity for both thought dimensions and then computed the difference between task-relatedness and thought orientation. A one-sample t-test was used to compare the distribution of these 1000 differences to 0, indicating whether task-relatedness or thought orientation contributed more to the topographic similarity during slow and fast finger tapping. **(C) Difference in the impact between task-relatedness and thought orientation.** We observed a double dissociation between the two thought dimensions. Specifically, during fast finger tapping, the impact of task-relatedness on topographic similarity was significantly greater than that of thought orientation. Conversely, during slow finger tapping, thought orientation shows a stronger impact than task-relatedness on topographic similarity. **(D) Double dissociation between task relatedness and orientation revealed by permutation analysis.** During fast finger tapping, topographic similarity was more strongly influenced by task-relatedness than by thought orientation. In contrast, during slow finger tapping, thought orientation exerted a greater influence on topographic similarity than task-relatedness. The red solid line represents the observed difference, while the blue dashed lines indicate the upper and lower edges of the 95% confidence interval of the permutation distribution. **Note:** Error bars represent SEM; SI: standard interval; PE: precision error; ***: p<0.001.

Neural Level: Nonlinear Contributions to the Double Dissociation Between Thought Dimensions and Topographic Similarity

Initial linear regression revealed a double dissociation: task-relatedness correlated with topographic similarity under fast tapping, while orientation was associated under slow tapping. To test for nonlinear contributions, we applied LMMs and GAMs. In the fast condition, the task-relatedness effect in the LMM (Beta = 0.0004, t = 2.57, 95% CI [0.0001, 0.0008]) disappeared after removing nonlinear components (Beta = 0.000, t = -0.24, 95% CI [-0.0004, 0.0003]), with GAM confirming strong nonlinearity (edf = 3.74, p = 0.001). Orientation showed a weak, nearly linear pattern (edf = 1.00, p = 0.04). In the slow condition, though not significant, task-relatedness remained linear (edf = 1.00, p = 0.16), while orientation showed nonlinearity (edf = 3.15, p = 0.37) (see Supplementary Table 7 for the detailed results, including effect size, SE and 95%).

Bayesian mediation analyses further confirmed this dissociation. Under fast tapping, task-relatedness showed a significant indirect effect on topographic similarity (mean = 0.14, 90% CI [0.08, 0.20]), with no direct effect, indicating a nonlinear mediation pathway. Orientation showed no credible mediation despite a large numerical estimate. Under slow tapping, only orientation yielded a small but credible indirect effect (mean = 0.01, CI [0.01, 0.02]); task-relatedness effects were non-significant and unstable (see supplementary table 8 for the mediation results). Model convergence issues in the slow condition for task-relatedness ($\hat{r} > 1.1$) were traced to perfect collinearity (r = 1.00) between the predictor and its smooth term, implying an essentially linear relationship (Supplementary Table 9).

Together, these results demonstrate a nonlinear double dissociation: task-relatedness nonlinearly predicts topographic similarity only at short timescales, while orientation does so only at long timescales.

ERSP Results: Beta–Gamma Power Tracks Behavioral Precision in Fast Tapping but Not Thought

To examine time-frequency dynamics, we conducted cluster-based permutation tests comparing fast and slow tapping conditions at Fz, Cz, and Pz (1000 permutations, cluster threshold $|t| > 2.0$). Each electrode revealed four significant clusters ($p < 0.05$, corrected), primarily within the beta/gamma (13-40 Hz) and theta (3-8 Hz) ranges. Fast tapping elicited greater high-frequency power both before (-800 to 0 ms) and after tapping (230-798 ms), while theta-band differences spanned pre- and early post-movement windows.

We then assessed correlations between ERSP power and PE using cluster-based permutation analysis ($r > 0.2$, 1000 permutations). Under the fast tapping condition, significant clusters were found at all electrodes—especially at Fz (e.g., 3-32.4 Hz, -800 to -450 ms; 10.6–39.2 Hz, 202–798 ms; $p < 0.001$). Cz and Pz also showed multiple beta-range clusters in the similar time and frequency periods. In contrast, the slow condition yielded no significant clusters at any electrode, suggesting that the association between ERSP power and PE is specific to the fast tapping condition, particularly within high-frequency bands around movement execution.

In contrast, no significant ERSP–thought correlations were observed at any electrode or condition, indicating that oscillatory power does not reliably track subjective thought dimensions in this context. All ERSP results are shown in supplementary figure 7-9

Thought is associated with phase dynamics rather than power changes

To elucidate the neural mechanisms underlying thought, we investigated whether its influence on neural oscillatory activity is mediated by phase dynamics rather than power fluctuations. This inquiry was prompted by the absence of robust associations between thought and conventional ERSP markers.

To investigate phase-based mechanisms, we computed the phase locking value (PLV) between finger taps. A PLV peak within 0–300 ms post-tap was observed under both tapping conditions (Figure 5A), mirroring the topographic similarity profile. Mean PLV in this window strongly correlated with absolute topographic similarity (fast: r(80) = 0.92; slow: r(80) = 0.90; both p < 0.0001; Figure 5B). Because topographic similarity includes negative values (especially in slow tapping, supplementary figure 10A), we used its absolute values and excluded ±3 SD outliers to avoid piecewise distortions. These findings suggest that topographic similarity reflects a phase-based, not amplitude-driven.

To validate this, we performed phase-shuffling. Both the 0–300 ms PLV and topographic similarity peaks disappeared (Supplementary figure 10 B & C), and their correlations with PE were abolished (fast tapping: r(80) = -0.02, p = 0.880; slow tapping: r(80) = -0.03, p = 0.745; Supplementary figure 10D). Likewise, all thought–similarity correlations became non-significant (all $p_{fdr(3)} = 1.00$; task-relatedness during fast tapping: r(94) = 0.16; orientation during fast tapping: r(98) = 0.06; task-relatedness during slow tapping: r(91) = 0.14; orientation during slow tapping: r(98) = 0.17; Figure 5C), confirming that intact phase structure is necessary for thought-related neural dynamics.

In conclusion, these findings suggest that the relationship between thought and neural oscillatory activity is mediated primarily by phase dynamics rather than power changes.

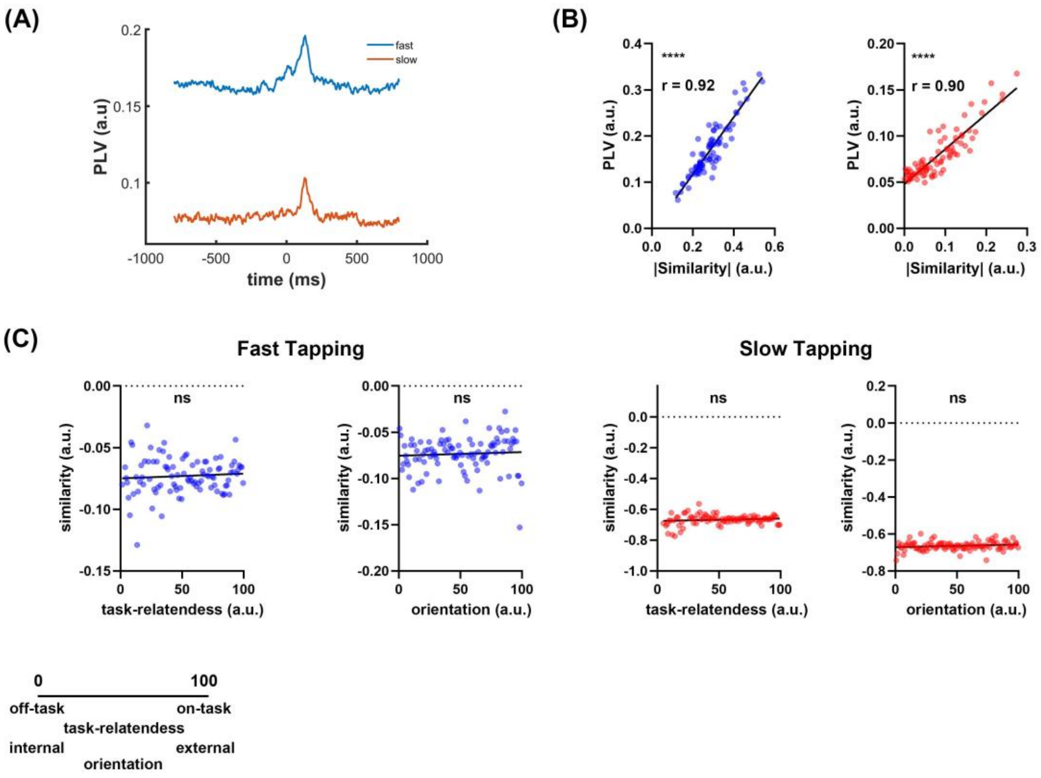


Figure 5. Phase-based neural dynamics underlie topographic similarity and its association with thought. (A) Grand-averaged PLV across trials and electrodes under fast and slow tapping

conditions. A distinct PLV peak emerged within the 0–300 ms post-stimulus window in both conditions, aligning with the topographic similarity peak. (B) Scatterplots showing the strong positive correlation between mean PLV (0–300 ms) and absolute topographic similarity across participants, indicating that topographic similarity is grounded in phase synchrony. (C) Correlation plots between topographic similarity and thought probe ratings (task-relatedness and orientation) under fast and slow tapping after phase shuffling. The original correlations disappeared following phase randomization, suggesting that phase dynamics are essential to the link between neural activity and thought.

Replication of main findings in an independent dataset

Behavioral level: Thought orientation occupies longer timescale than task-relatedness.

The second dataset was collected to replicate the result. The same as in the first dataset, we first applied paired sample T-tests to compare task-relatedness and thought orientation probe scores in all resting state and fast and slow finger tapping. The results show that in all three tasks, the participant's scores for thought orientation were significantly lower than task-relatedness (resting state: $t(34) = 8.24$, $p < 0.001$; fast FT: $t(34) = 4.59$, $p < 0.001$; slow FT: $t(34) = 4.88$, $p < 0.001$, Supplementary Figure 11). Then, we conducted a Friedman test, which revealed no significant differences in the counts of the four combinations of thoughts (on-internal, on-external, off-internal, off-external) during the resting state (Friedman statistic = 0.55, $p = 0.909$, Supplementary Figure 12). Although significant differences were found among the four groups during both fast and slow finger tapping (fast: Friedman statistic = 10.00, $p = 0.019$; slow: Friedman statistic = 18.78, $p < 0.001$; Supplementary Figure 12), multiple comparison tests showed no significant pairwise differences between the four categories in either fast or slow finger tapping (all $p > 0.05$; Supplementary Figure 12). These results suggest that, as in the main data set, while there is some degree of correlation between task-relatedness and thought orientation, there is no strict correspondence between on-task and external thoughts, nor between off-task and internal thoughts. Accordingly, consistent with the results of the first data set, we again show that task-relatedness and thought orientation are different dimensions on the cognitive level.

Finally, as replication, the absolute value PE was not significantly different between fast and slow FT ($t(34) = 0.39$, $p = 0.698$; Supplementary Figure 13). In addition, we replicated the double dissociation of the correlation between PE and thought: slow speed FT was only related with thought orientation ($r(98) = -0.42$, $p_{fdr(3)} < 0.001$) but not with task-relatedness ($r(95) = 0.01$, $p_{fdr(3) =} 1.000$; Supplementary Figure 14). While fast FT PE is only related with task-relatedness ($r(94) = -0.27$, $p_{fdr(3) =} 0.0084$) but not thought orientation ($r(98) = -0.15$, $p_{fdr(3)} = 1.000$; Supplementary Figure 14).

To account for individual variability, we applied LMMs and GAMs. Under the fast tapping condition, task-relatedness initially showed a significant negative association with PE (Beta = -0.0009, t = -3.89, 95% CI [-0.0013, -0.0004]), which became non-significant after accounting for nonlinearity (adjusted LMM: Beta = -0.0003, t = -1.20, 95% CI [-0.0007, 0.0002]; GAM: edf = 2.29, p = 0.03), replicating the nonlinear masking pattern seen in the main dataset. Orientation showed no initial effect (Beta = -0.0001, t = -0.42, 95% CI [-0.0005, 0.0003]) but revealed a significant negative association after adjustment (adjusted LMM: Beta = -0.0003, t = -1.33, 95% CI [-0.0007, 0.0001]; GAM: edf = 3.75, p = 0.01), consistent with its previously observed linear trend. Under the slow tapping condition, task-relatedness again had a significant initial effect (Beta = -0.0007, t = -3.53, 95% CI = [-0.0011, -0.0003]), which was strongly reduced after nonlinear adjustment (adjusted LMM: Beta = -0.0001, t = -0.50, 95% CI = [-0.0005, 0.0003]; GAM: edf = 6.10, p < 0.0001). Orientation showed a reversed pattern: initially negative (Beta = -0.0007, t = -3.35, 95% CI [-0.0011, -0.0003]), but significantly positive after controlling for nonlinearity (adjusted LMM: Beta = 0.0005, t = 2.64, 95% CI [0.0001, 0.0009]; GAM: edf = 1.00, p < 0.0001), reaffirming its robust linear role. See Supplementary Table 10 for the results.

Bayesian mediation analyses supported these findings. Task-relatedness showed significant negative indirect effects on PE in both tapping conditions (fast: -0.13, CI [-0.21, -0.04]; slow: -0.11, CI [-0.15, -0.08]), while direct effects were non-significant, confirming a suppression effect. For orientation, a modest positive indirect effect emerged in the fast condition (0.03, CI [0.02, 0.06]). In the slow condition, a large positive direct effect (0.35, CI [0.30, 1.11]) and a negative but non-significant indirect effect (-0.54, CI [-1.29, 0.11]) suggested potential suppression, though severe multicollinearity (r = -1.00) limits interpretability. See Supplementary Table 11 & 12 for the results

Interaction GAMs further confirmed condition-specific nonlinear patterns. Task-relatedness showed stronger nonlinearity in slow tapping (edf = 6.46, F = 8.23, p < 0.0001) than in fast tapping (edf = 2.21, F = 2.85, p = 0.043), with a significant condition interaction (F = 9.66, p < 0.0001). Orientation was nonlinear in fast tapping (edf = 3.44, F = 2.98, p = 0.019) but linear in slow tapping (edf = 1.00, F = 19.68, p < 0.0001), with a robust interaction effect (F = 160.62, p < 0.0001). This pattern replicates the double dissociation observed in the main dataset. See Supplementary Table 13 for the results

Taken together, these results indicate that the nonlinear relationship between task-relatedness and PE suppresses its overall effect, with this suppression being more pronounced under the slow tapping condition. In contrast, orientation contributes to PE in a consistent and robust linear fashion, and this linear effect may become more detectable when the influence of task-relatedness is masked by nonlinearity. These findings replicate the main dataset.

Neural level: Topographic similarity is impacted by task-relatedness at short intervals and by thought orientation at long intervals.

In the second dataset, we replicate that the topographic similarity during fast finger tapping was significantly higher than during slow finger tapping ($t(34) = 13.54$, $p < 0.001$, Supplementary Figure 15A); Next, we also replicate the significant correlation between topographic similarity and the PE in both slow and fast finger tapping conditions (fast: $r(33) = 0.66$, $p_{fdr(1)} < 0.001$; slow: $r(32) = 0.76$, $p_{fdr(1)} < 0.001$, Supplementary Figure 15B). Furthermore, the correlation between the task-rest difference of topographic similarity and PE was also replicated (fast: $r(33) = 0.66$, $p_{fdr} < 0.001$; slow: $r(32) = 0.74$, $p_{fdr} < 0.001$, Supplementary Figure 15C).

Finally, we also replicate the double dissociation between the impact of thought dimension on topographic similarity. The double dissociation is firstly shown in the correlation between thought dimensions and task-rest difference of topographic similarity. Specifically, for fast finger tapping, task-rest difference of topographic similarity is correlated with task-relatedness ($r(94) = 0.25$, $p_{fdr(3)} = 0.026$) but not thought orientation ($r(98) = 0.11$, $p_{fdr(3)} = 1.000$, Supplementary Figure 15D). Whereas for slow finger tapping, task-rest difference of topographic similarity correlates only with thought orientation ($r(91) = -0.46$, $p_{fdr(3)} < 0.001$) but not with task-relatedness ($r(95) = 0.13$, $p_{fdr(3)} = 1.000$; Supplementary Figure 15D). During fast FT, task-relatedness has a greater influence than thought orientation on topographic similarity, whereas during slow FT, thought orientation has a greater influence than task-relatedness (fast: mean =0.11, SD = 0.13, SEM = 0.004, $t(98) = 26.61$, $p < 0.001$; slow: mean = -0.12, SD = 0.16, SEM = 0.005, $t(98) = 23.35$, $p < 0.001$, Supplementary Figure 15E).

Neural level: thought impact topographic similarity through nonlinear way and its phase-based mechanisms

We reanalyzed neural-level effects in the replication dataset to assess the previously observed double dissociation between thought dimensions and topographic similarity. Under fast tapping, task-relatedness showed a significant positive effect (Beta = 0.0006, t = 2.40, 95% CI [0.0001, 0.0011]) that became non-significant after controlling for nonlinearity (Beta = -0.0002, t = -0.83, 95% CI [-0.0007, 0.0003]), with strong nonlinearity confirmed (edf = 4.31, $p < 0.001$). Orientation shifted from a weak positive effect (Beta = 0.0002, t = 0.71, 95% CI [-0.0003 0.0007]) to a significant negative association (Beta = -0.0006, t = -2.23, 95% CI [-0.0011, -0.0001]), with moderate nonlinearity (edf = 3.96, p = 0.0001). In slow tapping, task-relatedness was initially non-significant (Beta = 0.0000, t = -0.12, 95% CI [-0.0006 0.0006]) but became more negative after adjustment (Beta = -0.0005, t = -1.55, 95% CI [-0.0011, 0.0001]), with mild nonlinearity (edf = 2.80, p = 0.165). Orientation shifted from weakly positive (Beta = 0.0004, t = 1.18, 95% CI [-0.0002. 0.0010]) to significantly negative (Beta = -0.0007, t = -2.19, 95% CI [-0.0013, -0.0001]), with strong nonlinearity (edf = 4.16, $p < 0.001$). See Supplementary Table 14 for the detailed results.

Bayesian mediation analyses confirmed these nonlinear effects. In the fast condition, task-relatedness showed a significant indirect effect (mean = 0.186, 90% CI [0.124, 0.251]), with non-significant direct (-0.030, [-0.124, 0.063]) and significant total effects (0.156, [0.085, 0.227]). Orientation also showed a significant indirect effect (0.181, [0.115, 0.249]), with non-significant direct (-0.033, [-0.132, 0.067]) and total effects (0.149, [0.075, 0.224]). In the slow condition, task-relatedness showed a significant indirect effect (0.137, [0.053, 0.219]), non-significant direct (-0.069, [-0.179, 0.040]), and marginal total effect (0.068, [-0.005, 0.141]). Orientation exhibited significant indirect (0.209, [0.143, 0.278]) and total (0.181, [0.106, 0.255]) effects, with non-significant direct effect (-0.029, [-0.128, 0.069]). See Supplementary Table 15 for the detailed results.

Since the Bayesian mediation analyses did not reveal a clear double dissociation effect, we further employed a permutation test to compare the strength of the indirect effects. The results confirmed a double dissociation in indirect effect strength: task-relatedness exceeded orientation in the fast condition ($\Delta = 0.0283$, $p < 0.001$), while orientation dominated in the slow condition ($\Delta = -0.0726$, $p < 0.001$).

ERSP results confirmed beta-band power increases under fast tapping, with multiple significant clusters at Fz (e.g., 12.1–33.2 Hz, -800 to -480 ms, p = 0.001), Cz (e.g., 10.6–35.5 Hz, -944 to -508 ms, p = 0.003), and Pz (e.g., 9.8–33.2 Hz, -944 to -508 ms, p = 0.007). Cluster-based correlations revealed that only fast tapping ERSP clusters correlated with PE (e.g., Fz: 3–40 Hz, -554 to 336 ms, $p < 0.001$); no significant PE or thought correlations emerged in slow tapping (all $p > 0.05$). See Supplementary Figure 16-18 for ERSP results.

PLV also showed strong correlation with the absolute value of topographic similarity (fast: r(33) = 0.72, $p < 0.0001$; slow: r(33) = 0.77, $p < 0.0001$; supplementary figure 19A). Phase-shuffling abolished all correlations between topographic similarity with PE (fast: r(32) = -0.07, p = 0.680; slow: r(32) = -0.04, p = 0.812; supplementary figure 19B). Although phase-shuffled topographic similarity showed a significant correlation with task-relatedness under the fast tapping condition (r(94) = 0.28, $p_{fdr(3)} = 0.026$; supplementary figure 19C), no significant correlations were observed in any other condition (all $p_{fdr(3)} > 0.07$; supplementary figure 19C). This isolated effect was not present in the main dataset, suggesting that the relationship between phase-shuffled topographic similarity and thought is not robust. This confirms that topographic similarity is phase-based, and that thought-related effects rely on an intact phase structure.

Discussion

By investigating how different dimensions of thought interact with behavioral and neural timescales, we demonstrate that: **1)** at the cognitive level, the thought orientation dimension differs from the task-relatedness dimension in terms of their subjective ratings; **2)** at the behavioral level, as tested by finger tapping, the thought orientation dimension is associated with longer timescales (slow finger tapping), whereas the task-relatedness dimension is associated with shorter timescales (fast finger tapping); **3)** at the neural level, topographic similarity is associated with the thought orientation dimension over longer periods of time, and by task-relatedness over shorter time periods; **4)** the distinct nonlinear mechanisms underlying the relationship between thought dimensions and both behavioral and neural timescale measures; **5)** the phase-based nature of topographic similarity, highlighting the central role of inter-regional neural synchrony. Together, these findings reveal that the dimensions of task-relatedness and thought orientation operate at different behavioral and neuronal timescales.

Task-relatedness and thought orientation operate in dissociable timescales at the behavioral level

We first use self-paced finger tapping at both slow and fast tempos to measure the timescales of task-relatedness and thoughts orientation at the behavioral level. Our results show that task-relatedness is related to the shorter timescale during fast finger tapping, whereas thought orientation is related to the longer timescale during slow finger tapping. This suggests that thought orientation operates at slow behavioral timescales. More specifically, the stronger the external nature of thought, the lower the PE at longer timescales (slow finger tapping). By contrast, thought-relatedness operates at fast behavioral timescales. More specifically, the stronger the "on-task" nature of thought, the lower PE at shorter timescales (fast finger tapping). Thus, we observe double dissociation for task-relatedness and thought orientation with respect to short vs. long timescales. Importantly, this double dissociation cannot be attributed to systematic differences in task difficulty or motor accuracy across tapping speeds. PE did not significantly deviate from zero in either fast or slow tapping, nor did it differ between the two conditions. This indicates that participants maintained comparable overall tapping accuracy across tempos, and that the observed relationships between PE and thought dimensions reflect trial-by-trial variability around a stable motor baseline rather than global performance drift. Thus, spontaneous thought shapes the temporal precision of behavior without inducing gross motor failure.

LMM and GAM analyses further elucidated the dynamic underpinnings of the observed behavioral effects, revealing a nonlinear suppression effect for task-relatedness. Specifically, the nonlinear trend masked the initially observed linear association between task-relatedness and PE, particularly under slow tapping conditions. In contrast, thought orientation maintained robust linear associations with PE across both fast and slow tapping, suggesting a distinct temporal profile (see figure 6A for an example).

Bayesian mediation analyses confirmed these differential patterns, indicating a predominantly indirect, nonlinear pathway for task-relatedness and a primarily direct, linear pathway for orientation. This mechanistic distinction offers a compelling explanation for the behavioral double dissociation: during fast tapping, the relatively weak nonlinearity in the task-relatedness–PE relationship allowed a linear model to detect the effect. However, under slow tapping, the nonlinear structure obscured the linear association, particularly around task-relatedness VAS scores near 50—corresponding to ambiguous transitions between on-task and off-task states. As shown in Supplementary Figure 20, this ambiguity increased behavioral variance, reflecting a lack of robust temporal integration in task-relatedness at longer timescales. By contrast, the lower degree of nonlinearity during fast tapping suggests that task-relatedness supports temporal segregation by segmenting input over shorter durations. Meanwhile, the consistent linear association between thought orientation and PE, even in slow tapping, indicates stronger temporal integration.

Together, these findings suggest that task-relatedness and orientation engage distinct temporal processing mechanisms: task-relatedness supports short-timescale facilitating temporal segregation, while orientation facilitates long-timescale enabling temporal integration. Our behavioral results are in accordance with previous data showing that off-task thought exhibits larger variability in reaction time (Kucyi et al., 2016) which, in our findings, is reflected in an increased PE in off-task thought compared to on-task thought. The current findings also show that variability (measured by the PE) across short vs. long timescales, is associated with the distinct thought dimensions of task-relatedness and thought orientation. This effect may arise from natural differences in the temporal integration length of these thought dimensions requiring different degrees of temporal integration. Given that thought orientation is related to slow finger tapping, we assume that it requires integration of information over a longer duration, and thus a longer timescale, whereas task-relatedness information is integrated over a shorter timescale.

Task-relatedness and thought orientation operate in dissociable timescales at the neural level

What about the timescales of thought at the neural level? We measured topographic similarity, as it directly quantifies the moment-to-moment temporal dynamics of EEG topography, and in particular, the influence of the past on the present (Luo et al., 2024). We first show that topographic similarity is related to the PE at both shorter (fast finger tapping) and longer (slow finger tapping) timescales. Higher topographic similarity was consistently correlated with higher PE in both fast and slow finger tapping conditions. This indicates, as we expected, that the precision of tapping behavior is closely linked to the duration of neural activity over distant time points reflecting temporal integration of inputs across the different points in time.

Most importantly, the observed double dissociation of **thought dimension** (task-relatedness vs. thought orientation) and **timescale** (short vs. long) at the neural level, suggest that these two thought dimensions may preferentially engage distinct neural mechanisms, depending on the task at hand. More specifically, topographic similarity during fast finger tapping was associated with task-relatedness whereas slow finger tapping was related to thought orientation. This suggests that, at shorter timescales, the influence of the preceding information is mediated by how on-task the individual is at the moment. More broadly speaking, this also indicates that the integration of information in the task-relatedness thought dimension occurs over a shorter timescale than thought orientation. Conversely, at longer timescales, the influence of the preceding information is mediated by how internally or external orientated the individual is at the moment. More broadly speaking, this suggests that the integration of information in the thought orientation dimension occurs over a longer timescale than task-relatedness. Notably, these thought–neural associations were absent during the resting state, even when topographic similarity was computed using identical temporal windows matched to fast and slow tapping intervals. Neither task-relatedness nor thought orientation correlated with resting-state topographic similarity at either timescale. This absence indicates that the coupling between spontaneous thought and neural timescales is not a static or trait-like property, but instead emerges specifically when thought unfolds in interaction with an ongoing task structure. In this sense, task context appears to gate the expression of thought-related neural dynamics, enabling temporal alignment between cognition and neural integration only when behavior imposes explicit temporal constraints.

LMM and GAM analyses at the neural level further elucidated the underlying mechanisms, revealing distinct nonlinear mediation effects. Specifically, during fast tapping, task-relatedness nonlinearly influenced topographic similarity, whereas during slow tapping, stimulus orientation exerted a nonlinear influence. Importantly, we observed that the neural mechanisms by which thought influences behavior diverge significantly from its behavioral counterparts. This discrepancy is likely attributable to our use of topographic similarity at the neural level—a metric that directly quantifies the influence of preceding tapping on subsequent tapping. Crucially, this influence exhibits a non-additive, that is, nonlinear nature (Huang et al., 2017; Northoff, Zilio, et al., 2024; Wainio-theberge et al., 2020; Wolff, de la Salle, et al., 2019).

Conventional theories typically assume additive effects of pre-stimulus processes on post-stimulus neural responses (Barron et al., 2011; Christoff et al., 2016; Smallwood & Schooler, 2006). However, the non-additive perspective challenges this view. Emerging evidence suggests that pre-stimulus alpha power and its variability significantly regulate the reduction of trial-to-trial variability (TTV) in post-stimulus periods—a phenomenon known as TTV quenching, which has been proposed as a key neural mechanism underlying the influence of thought (Huang et al., 2017; Northoff, Zilio, et al., 2024; Wainio-theberge et al., 2020; Wolff, de la Salle, et al., 2019). In our study, the nonlinear analytic framework supports this non-additive relationship. Notably, because our finger-tapping paradigm was free of external stimuli, we interpret this nonlinear relationship between preceding and subsequent tapping as a manifestation of cross-temporal information integration (Figure 6).

Task-relatedness is associated with temporal segregation while thought orientation requires temporal integration

We suppose that the different timescales of task-relatedness and thought orientation are key to the temporal integration of inputs/outputs and their associated information processing (Golesorkhi, Gomez-Pilar, Tumati, et al., 2021; Gomez-Pilar et al., 2018; Kolvoort et al., 2020; Wolman et al., 2023). Fast finger tapping may require more frequent neural updates and shorter timescales to integrate information over time. This would also support temporal segregation of information, which segments longer durations into smaller intervals, allowing us to focus on and process the current task (e.g., to be more “on-task”) more automatically (Lechner & Northoff, 2023; Pöppel, 2009; Thönes & Stocker, 2019).

By contrast, slower finger tapping may allow for more introspective or reflective thoughts (e.g., to be more internally-oriented), , which are supported by memory systems, and require longer neural integration periods (Lechner & Northoff, 2023; Pöppel, 2009; Thönes & Stocker, 2019). We therefore assume that the distinct timescales of task-related and thought orientation reflect different degrees of temporal input information integration. Shorter timescales are more limited, and therefore facilitate the temporal segregation of sequential inputs focusing on the most immediate inputs, resulting in a focus on the task and increased attention. While longer timescales allow for more temporally distant input information integration from memory to the present – this facilitates internal thoughts (Figure 6).

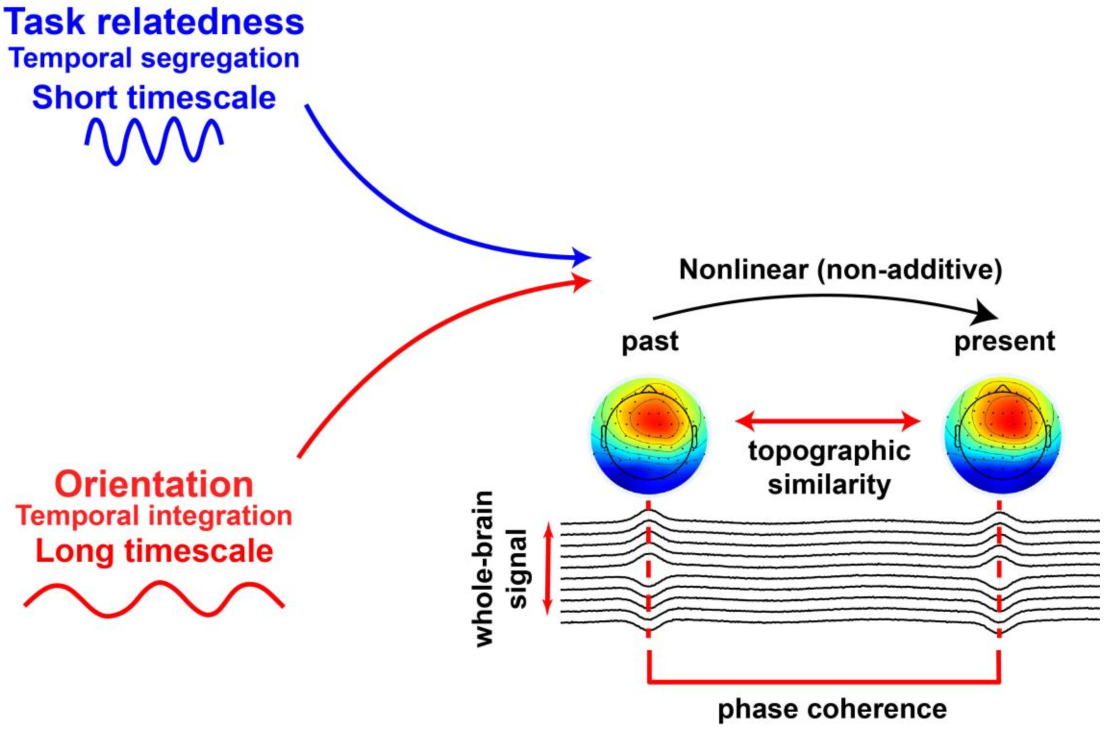


Figure 6. Schematic of the proposed neural mechanism underlying the double dissociation. Task-relatedness is associated with topographic similarity during fast tapping (short timescale), indicating its relationship with temporal segregation. Thought orientation is associated with topographic similarity during slow tapping (long timescale), reflecting its relationship with temporal integration windows. These effects reveal distinct, non-additive phase-based neural mechanisms for the two thought dimensions across temporal scales.

Our topographic similarity results demonstrated a robust double dissociation between task-relatedness and orientation across conditions. Crucially, we found that topographic similarity was tightly coupled with PLV, and that disrupting phase structure abolished its relationship with thought content. This indicates that the observed neural patterns are fundamentally phase-based. Together with prior work (Hua et al., 2022; Long et al., 2025), these results suggest that spontaneous thought itself may be structured by phase dynamics. This supports a growing view that the neural encoding of internally directed cognition depends on distributed, phase-based synchrony, rather than localized amplitude-based signals (Christoff et al., 2016; Groot et al., 2022; Murphy, Poerio, et al., 2019; Northoff, Zilio, et al., 2024). Crucially, this phase-based interpretation is further constrained by the absence of reliable associations between oscillatory power and subjective thought dimensions. Although time–frequency analyses revealed robust beta–gamma power was associated with behavioral precision during fast tapping, no ERSP measures reliably tracked either task-relatedness or thought orientation. This dissociation indicates that oscillatory power primarily reflects motor execution and performance demands, whereas subjective thought states are not indexed by local amplitude fluctuations. Instead, spontaneous thought appears to rely on distributed, phase-based coordination across time. Importantly, this null finding is theoretically informative rather than incidental, as it delineates a functional boundary between power-sensitive motor processes and phase-sensitive cognitive dynamics.

Limitations

We conducted these analyses on two independent datasets, and the main findings—including the double dissociation between thought dimensions and timescales at both behavioral and neural levels—were fully replicable. In both datasets, the nonlinear mechanisms underlying these dissociations, as revealed by LMMs and GAMs, were also consistently observed. This convergence across analytical approaches and datasets reinforces the robustness and generalizability of our findings. Nonetheless, several limitations should be acknowledged.

First, the gender distribution in the second dataset was not perfectly balanced, which may have introduced potential gender-related sampling bias.

Second, while our findings strongly suggest functional separability between task-relatedness and thought orientation, both dimensions were inferred from VAS ratings, which are moderately correlated. However, the consistent double dissociation observed across behavior and EEG indicates that the two dimensions are associated with distinct processes, despite their subjective correlation.

Third, we did not directly measure thought dynamics. Instead, we inferred them through subjective reports and their interactions with long and short timescales, assessed via finger tapping and topographic similarity. While this is a common challenge in the field of thought research, where direct measurement is generally not feasible, we acknowledge that causal evidence (e.g., via experimental manipulation or intervention) would further strengthen our claims. However, the converging evidence from two independent datasets already provides compelling support for the underlying distinction. In addition, we employed Bayesian mediation analyses to examine whether the nonlinear mechanisms served as intermediaries in the relationship between thought and both PE and topographic similarity. While we are fully aware that mediation models do not establish true causality, they can nonetheless offer valuable insights into potential causal pathways and help uncover the latent structure of these thought–timescales (behavioral and neural) associations.

Fourth, our study focused on a single task—finger tapping—which may raise concerns about generalizability to other cognitive domains. That said, finger tapping is particularly well-suited for probing timescale-dependent dynamics due to its continuous and temporally structured nature (Bastian & Sackur, 2013; Groot et al., 2022; Kutz et al., 2022; Petilli et al., 2018). In future studies, we plan to incorporate a broader range of experimental paradigms—such as the Sustained Attention to Response Task (SART), go/no-go tasks, and simple reaction time paradigms—to further test the generalizability of our findings. Specifically, we aim to examine whether the distinct timescales associated with different dimensions of thought can be consistently observed across diverse cognitive tasks. This approach will substantially extend the scope of the present work and strengthen the theoretical validity of our framework.

Finally, given that thought evolves continuously over time (Rostami et al., 2022; Vanhaudenhuyse et al., 2011), if different dimensions of thought operate on distinct timescales, there should theoretically exist a transition point or intersection between them. However, as distinguishing thought dimensions based on their temporal characteristics is a relatively novel approach, the present study focused on two thought dimensions—task-relatedness and thought orientation—that we hypothesized to differ substantially in timescale, and tested them using two discrete tapping speeds (0.8 s and 1.9 s). While our findings support a dissociation, with task-relatedness associated with shorter timescales and orientation with slower ones, we acknowledge that using only two tapping speeds limits the granularity with which we can capture the transitional dynamics between thought states. In future work, we plan to address this by employing paradigms that allow for continuous variation in tapping speed, enabling a more fine-grained characterization of temporal transitions between distinct cognitive states.

Together, these limitations do not undermine the core conclusions of our study, but rather point to important directions for future research.

Conclusion

Altogether, we demonstrate a double dissociation of two thought dimensions in their timescale at both the behavioral and neural levels. Task-relatedness operates at a shorter timescale, whereas thought orientation operates at a longer timescale. This supports the conclusion that task-relatedness (on vs. off-task) and thought orientation (internal vs. external) are indeed distinct dimensions of thought, which are processed along different durations (short vs. long) thus reflecting distinct timescales.

Overall, these findings offer valuable insights into how thought processes are associated with different timescales and thus entail varying temporal frameworks. This deepens our understanding of the temporal structure and temporal dynamics of thought; that is, thought dynamics (Rostami et al., 2022). This temporal and ultimately spatiotemporal approach to understanding thought is consistent with the recently introduced novel umbrella framework of ‘Spatiotemporal Neuroscience’ (Northoff, 2024; Northoff et al., 2020a, 2020b, 2025).

STUDY 3

Phase dynamics as bridge between thought and behavior

published in:

Hua, J., Ge, X., Fogel, S., Zhang, J., & Northoff, G. (2025). Phase Dynamics as Bridge between Thought and Behavior. Journal of Cognitive Neuroscience, 1–19. https://doi.org/10.1162/JOCN.a.2417.

Abstract

Ongoing thoughts play a critical role in shaping cognitive performance, with phenomena such as mind-wandering consistently associated with decreased task accuracy and prolonged reaction times (RT). However, the neural mechanisms underlying the influence of thought dimensions on cognition and behavior remain unclear. To elucidate this, we used EEG to investigate how two key thought dimensions—deliberate control (deliberate vs. spontaneous thoughts) and task relatedness (on-task vs. off-task thoughts)—affect RT during a simple reaction time task. Behavioral results showed that both on-task and more deliberate thoughts were associated with shorter RTs compared to off-task and more spontaneous thoughts. Neurodynamic analyses revealed that on-task and deliberate thoughts were characterized by pre-stimulus increases in both frequency sliding (FS), reflecting faster phase-based neural speed, and sample entropy (SE), reflecting higher neural uncertainty/flexibility. Both pre-stimulus FS and SE were significantly related to the degree of post-stimulus inter-trial phase coherence (ITPC), which, in turn, correlated with RT. This sequential relationship suggests that phase-based neural dynamics play a crucial role in mediating the relationship of thought with task related behavior. Together, these findings suggest that phase-based neural dynamics could play a key role across the divide of pre- and post-stimulus activity in shaping the influence of ongoing thoughts (deliberate control and task relatedness) on task execution and its related behavior (RT).

Introduction

Human thought is highly dynamic, continuously shifting and evolving over time (Christoff et al., 2016; Girn et al., 2020; Hua et al., 2022; Kucyi et al., 2016; Rostami et al., 2022; Scalabrini et al., 2022; Smallwood, Bernhardt, et al., 2021; Smallwood, Turnbull, et al., 2021; Vanhaudenhuyse et al., 2011). For example, when “mind wandering” occurs, thoughts seamlessly transition between various contents, whereby attention drifts away from the current task-at-hand towards unrelated streams of thought (Franklin et al., 2011; Smallwood, Turnbull, et al., 2021; Smallwood & Schooler, 2006). During such states, the mind operates with remarkable freedom and fluidity, reflecting the dynamic nature of thought (Christoff et al., 2016, 2018; Girn et al., 2020). These fluctuations in the task-relatedness and spontaneity of our thoughts have been shown to influence task-related behaviors, such as reaction time (RT) (Alperin et al., 2021; Barron et al., 2011; Christoff et al., 2016; Girn et al., 2020; Smallwood & Schooler, 2006). Specifically, when the mind drifts away from the task at hand, RT tends to increase, whereas maintaining task-focused thoughts is associated with shorter RTs (Barron et al., 2011; Christoff et al., 2016; Smallwood & Schooler, 2006). Despite these insights, the mechanistic pathway that links ongoing thought with post-stimulus response behavior remains poorly understood, leaving a critical gap in our understanding of how thoughts shape behavior.

A key aspect in understanding this interplay is the multidimensional nature of thought. Traditionally, thought has been dissected into two dimensions—task relatedness (on-task vs. off-task) and deliberate control (deliberate vs. spontaneous) (Barron et al., 2011; Christoff et al., 2016, 2018; Smallwood & Schooler, 2006). The '*goal-directed hypothesis*' posits that deliberate control and task relatedness are inherently coupled, whereby spontaneous thought represents a failure of executive control to maintain task-focused attention, thus conflating off-task processing with spontaneous thought generation (Barron et al., 2011; Groot et al., 2022; Irving, 2016; Seli, Kane, Metzinger, et al., 2018; Smallwood & Schooler, 2006). While this framework predicts that such executive control failures manifest behaviorally as prolonged reaction times and diminished task performance (Seli, Kane, Metzinger, et al., 2018; Smallwood & Schooler, 2006), emerging empirical evidence challenges this unitary conceptualization. Specifically, recent findings demonstrate that deliberate control and task relatedness constitute dissociable cognitive dimensions, as evidenced by instances where thoughts can be simultaneously off-task and deliberately maintained (Mills et al., 2018). Therefore, in this study we divided thought into these two dimensions to investigate how thought interacts with neural dynamics, and task-related behaviors (**Figure 1**). Here, we investigated this overall goal in three separate aims (**Figure 1**). To achieve these aims, we employed a simple reaction time task (RTT), categorizing ongoing thoughts based on task relatedness (off-task vs. on-task) and deliberate control (spontaneous vs. deliberate).

Thought and Pre-stimulus Dynamics (Aim 1).

The first aim was to examine how the two thought dimensions, task relatedness and deliberate control, affect neuro-oscillation dynamics. Most task-based and event-related studies focus on evoked brain responses during the post-stimulus period (Barron et al., 2011; Polich, 2003; Smallwood & Schooler, 2006). However, it is important to also consider pre-stimulus with, for instance, its spontaneous brain oscillations which are known to impact post-stimulus activity and its related behaviors (He, 2013; Huang et al., 2017; Northoff, Buccellato, et al., 2024; Scalabrini et al., 2017). This is important for two reasons. First, there is strong evidence that thoughts are embedded and influenced by ongoing brain dynamics (Girn et al., 2017; Karapanagiotidis et al., 2018; Smallwood & Schooler, 2006). Secondly, pre-stimulus activity impacts post-stimulus activity (He, 2013; Huang et al., 2017; Wainio-theberge et al., 2020; Wolff, de la Salle, et al., 2019) including the latter's associated mental features (Wolff et al. 2019, Northoff et al. 2024).

Therefore, in this study, we specifically focused on the impact of ongoing thoughts on pre-stimulus neural oscillatory dynamics. We focused on two dynamic features: neural **speed** and neural **uncertainty**. Neural speed can be measured using **peak frequency sliding (FS)** , quantifying the rate of change in neural oscillatory activity—with higher FS indicating faster oscillations that reflect adaptive responses to cognitive demands (Cohen, 2014b, 2014a; Hua et al., 2022). Neural uncertainty, captured by sample entropy, measures the unpredictability of oscillatory patterns, where higher SE suggests greater signal variability that may support cognitive flexibility (Lau et al., 2022; Lechner & Northoff, 2023; Liu et al., 2018). We will examine how ongoing thought—integrating both task-relatedness and deliberate control—relates to these pre-stimulus oscillatory metrics.

To operationalize these measures, we chose to focus on the **alpha band (8–12 Hz)** for several reasons. First, alpha oscillations are central to cognitive control and attention, serving as an input gating mechanism that regulates the flow of task-relevant information, e.g., the input stream (Jensen & Mazaheri, 2010; Klimesch, 2012). Second, alpha oscillations have been shown to exhibit strong pre-stimulus dynamics that are known to predict post-stimulus performance (Foxe & Snyder, 2011; Northoff, Buccellato, et al., 2024; S. Palva & Palva, 2007). Lastly, alpha band activity is sensitive to both thought and stimulus effect (Hua et al., 2022; Northoff, Buccellato, et al., 2024), making it an ideal frequency range for investigating the interplay between ongoing thoughts and neural preparation for subsequent external stimulus/input processing (Klimesch, 2012). These attributes make the alpha band a robust temporal window to make sound a-priori hypotheses about the neural mechanisms underlying the impact of thoughts on behavior.

Most prior EEG studies of thought and cognition have emphasized stimulus-locked or whole-epoch activity (Barron et al., 2011; Polich, 2003; Smallwood & Schooler, 2006), thereby treating pre- and post-stimulus periods as a single analytic window. However, this approach risks obscuring the distinct functional contributions of these two periods. The pre-stimulus interval reflects the spontaneous, ongoing neural dynamics that form the preparatory context in which thoughts unfold and external input is received (He, 2013; Huang et al., 2017, 2017; Northoff, Buccellato, et al., 2024; Scalabrini et al., 2017; Wainio-theberge et al., 2020). In contrast, the post-stimulus interval reflects stimulus-driven neural responses and their direct relationship to behavioral performance (Barron et al., 2011; Polich, 2003; Smallwood & Schooler, 2006). By examining these periods separately, we are able to disentangle how ongoing thought shapes preparatory neural states before stimulus onset (Aim 1), and how these states subsequently influence stimulus-locked phase alignment and task execution (Aims 2 and 3). This methodological choice is therefore essential to reveal the mechanistic pathway from thought to behavior through neural dynamics.

Post-stimulus Dynamics: interaction with pre-stimulus dynamics (Aim 2) and relation to behavior (Aim 3).

Aims 2 and 3 address how pre-stimulus dynamics influence post-stimulus neuro-oscillation dynamics (aim 2) and behavior (aim 3). **In Aim 2**, we explored how pre-stimulus FS and SE influence post-stimulus inter-trial phase coherence (ITPC), which quantifies entrainment (Lakatos et al., 2019) as temporal alignment of neural oscillatory phases to the timing of the external stimuli across trials (Lechner & Northoff, 2023; Northoff et al., 2023; Rapela et al., 2018; Van Diepen & Mazaheri, 2018). We related FS and SE in the pre-stimulus period to ITPC in the post-stimulus period because we hypothesized that pre-stimulus neural oscillatory speed (indexed by FS) and uncertainty (indexed by SE) could influence the phase of neural oscillations at stimulus onset (indexed by ITPC). The post-stimulus phase coherence (ITPC), in turn, provides the ground for the brain's neural activity to reach the optimal state required for behavior with faster reaction times (Van Diepen & Mazaheri, 2018) . Such phase alignment subsequently affects the degree of neural oscillatory synchronization (Cohen, 2014b, 2014a; Lau et al., 2022), which shapes how the external input is processed including the subject's subsequent behavior, e.g., RT. Given this, we hypothesize that enhanced pre-stimulus dynamics will lead to increased ITPC. **In Aim 3,** we investigate the behavioral consequence of this enhanced ITPC by testing its impact on RT. Given that higher ITPC is associated with more efficient stimulus processing and on-task thoughts (Cohen, 2014a; Duprez et al., 2021; López et al., 2019; Rapela et al., 2018; Van Diepen & Mazaheri, 2018), we hypothesize that increased pre-stimulus FS and SE will be associated with higher post-stimulus ITPC, and that this will in turn lead to faster RT.

To formally test the sequential pathway hypothesized in Aims 1–3—namely, that ongoing thought influences pre-stimulus neural dynamics (FS, SE), which in turn impact post-stimulus phase coherence (ITPC) and ultimately shape reaction times (RT)—we employed various mediation model analyses. These models allowed us to go beyond pairwise associations and directly examine whether pre-stimulus FS and SE function as intermediaries between thought dimensions and post-stimulus outcomes, as well as whether ITPC mediates the link between pre-stimulus dynamics and behavioral performance. Given that the central claim of this study concerns how thought impacts behavior through neural dynamics, mediation analyses provide a principled and necessary framework to establish this mechanistic pathway.

To provide a clear analytic roadmap, we followed three primary hypotheses corresponding to our three aims.

Aim 1 (From thought to pre-stimulus dynamics): We hypothesized that the two thought dimensions—task relatedness and deliberate control—would differentially influence pre-stimulus oscillatory dynamics. Specifically, on-task and deliberate thoughts were expected to be associated with higher FS and higher SE.

Aim 2 (From pre- to post-stimulus activity): We hypothesized that enhanced pre-stimulus FS and SE would facilitate stronger phase-based temporal alignment at stimulus onset, as reflected in increased post-stimulus ITPC.

Aim 3 (From post-stimulus activity to behavior): We hypothesized that higher post-stimulus ITPC would be associated with shorter RT, thereby linking thought-related pre-stimulus dynamics to task execution.

Beyond these three hypotheses, we conducted exploratory analyses to test the interdependence of FS and SE by examining their correlation during the pre-stimulus period. In addition, we carried out post-hoc analyses to assess the robustness and specificity of the observed effects. These included (i) phase-shuffling controls to verify the phase-dependence of FS, SE, and their ITPC relationships; and (ii) resting-state analyses to evaluate whether the thought–neural dynamics associations were truly task-related. This structure enables us to clearly distinguish a priori hypotheses from exploratory and post-hoc extensions, while situating each analysis within the broader framework of the overall study goal.

Together, all three aims and hypotheses constitute a novel mechanistic pathway that links thoughts and ongoing neural dynamics (FS, SE) during the pre-stimulus period to post-stimulus phase coherence (ITPC) and task execution (RT) (Hanslmayr et al., 2006; Nakatani et al., 2021). Specifically, this study reveals that on-task and deliberate thoughts are associated with higher pre-stimulus FS and SE, which correlate with greater post-stimulus ITPC that by itself relates to shorter RT. These results underscore the influence of ongoing phase dynamics across the divide of pre- and post-stimulus activity including their relation to task performance on thoughts. We provide new insights into how our thoughts and behaviour are embedded in a highly influential neuro-oscillatory context of ongoing phase dynamics right at the interface of internal activity (pre-stimulus period) and external stimuli (post-stimulus period).

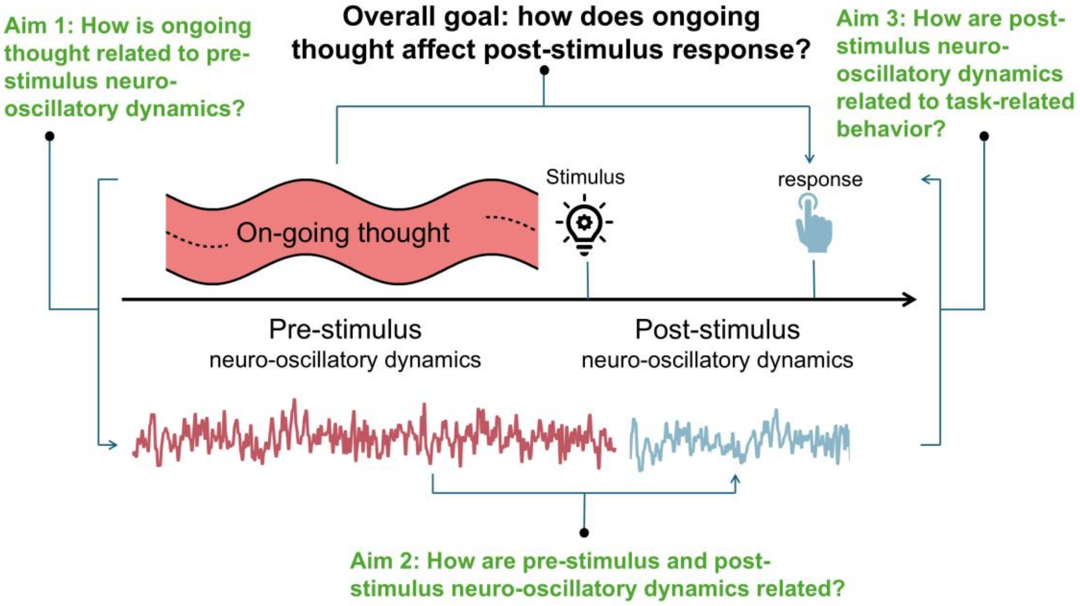


Figure 1: Conceptual framework of this study. Overall Goal: To examine how ongoing thought influences post-stimulus response through its interaction with pre-stimulus and post-stimulus neural oscillations. **Aim 1:** To investigate how ongoing thought dimensions (on-task deliberate vs. off-task spontaneous) are related to pre-stimulus oscillations, including FS and SE. **Aim 2:** Determine how pre-stimulus oscillations (FS and SE) interact with post-stimulus oscillations (ITPC). **Aim 3:** Explore how post-stimulus oscillations, particularly ITPC, relate to behavioral responses (reaction time, RT).

Methods

Participants

Forty right-handed adults participated in the study (13 female; age range = 18-33 years; mean age = 22.4 years, SD = 2.4 years). All had normal or corrected-to-normal vision and reported no neurological or psychiatric conditions that might affect performance (including, but not limited to, major depressive disorder, anxiety disorders, bipolar disorder, or schizophrenia). In addition, participants were instructed not to consume alcohol or engage in sleep deprivation on the day prior to the experiment. The experimental protocols were approved by the research ethics committee of the Zhejiang University and the University of Ottawa, and the study was carried out with their permission. Written informed consent was obtained from each participant prior to study participation.

The sample size (n = 40) was determined based on prior studies using EEG to investigate spontaneous thought and neural dynamics in similar paradigms (Barron et al., 2011; Girn et al., 2017; Hua et al., 2022), which typically included 25–40 participants. Additionally, a priori power analysis was conducted using G*Power 3.1 (Faul et al., 2007) to determine the required sample size for detecting medium effects (Cohen's $d = 0.5$) in paired-sample t-tests, which constitute the primary statistical tests in this study. The analysis indicated that a minimum of 34 participants would be required to achieve 80% power at $\alpha = 0.05$ (two-tailed). Accordingly, we recruited 40 participants, which provides sufficient statistical power to detect the hypothesized effects.

Procedures

The procedure consisted of two sessions conducted with EEG recording: (1) a resting-state session and (2) a simple reaction time task (RTT), each lasting 10 minutes. In order to remain consistent with previous investigations, and due to the related time constraints (i.e., 10 minute acquisitions), to ensure a longer pre-stimulus period (4s) to generate and assess ongoing thought (Rostami et al., 2022; Vanhaudenhuyse et al., 2011), both resting state and task sessions incorporated 20 thought probes, during which participants responded to two questions (**Figure 2A**). Although the number of trials is not very large, ITPC analysis can still be conducted, as a stable result can be obtained with more than 15 trials (Cohen, 2014a).

The resting-state session was performed first, where participants were instructed to fixate on a cross displayed on the screen and remain relaxed until prompted by a thought probe. The inter-probe interval (IPI) in the resting-state task varied from 5 to 65 seconds, with a jitter of 10 seconds (**Figure 2B**).

For the RTT, participants were required to respond upon detecting a color change. Significant interindividual variability in grey level difference judgments (Kuehni, 2009) was controlled for in this task (**Figure 2C**). Once the stimulus threshold was determined, the corresponding grey level was employed as the stimulus grey level in the RTT task.

The inter-trial interval (ITI) during the RTT task was determined in the same way as the IPI during the resting state (**Figure 2C**), the only difference being that a behavioural response was required for each probe **(Figure 2D)**. Thus, the resting state served as a control condition for task-preparatory states of thought. During the ITI, a fixation cross with a grey level of 100 (completely white) was presented. During the stimulus presentation period, the grey level transitioned gradually over 2000ms from white to the threshold grey level. Participants were instructed to press the space bar as quickly as possible upon detecting the fixation cross **(Figure 1C)**. After the stimulus period, the two thought probe questions were presented.

Thought probes

Thought probes are commonly utilized in the study of mind wandering, serving as a means to detect subjective thought states (Christoff et al., 2009; Franklin et al., 2011; Hua et al., 2022; Mills et al., 2018; Smallwood & Schooler, 2006). Two questions were posed during each probe, addressing two separate dimensions of thought: **1)** deliberate constraint, and, **2)** task-relatedness. Scores for thought probes were rated on a visual analog scale ranging from 0 to 100. Participants were instructed to select a score reflecting their state just before each thought probe. Specifically, for deliberate constraint, participants were asked: ‘Are you trying to control or pay specific attention to your thought or body movements?’, where 0 = spontaneous and 100 = deliberate. For task-relatedness, during the resting state, participants were asked: ‘Are you keeping your eyes on “+”?’, and during the RTT: ‘Are you focused on the task?’, where 0 = ‘off task’ and 100 = ‘on task’. (**Figure 1E**).

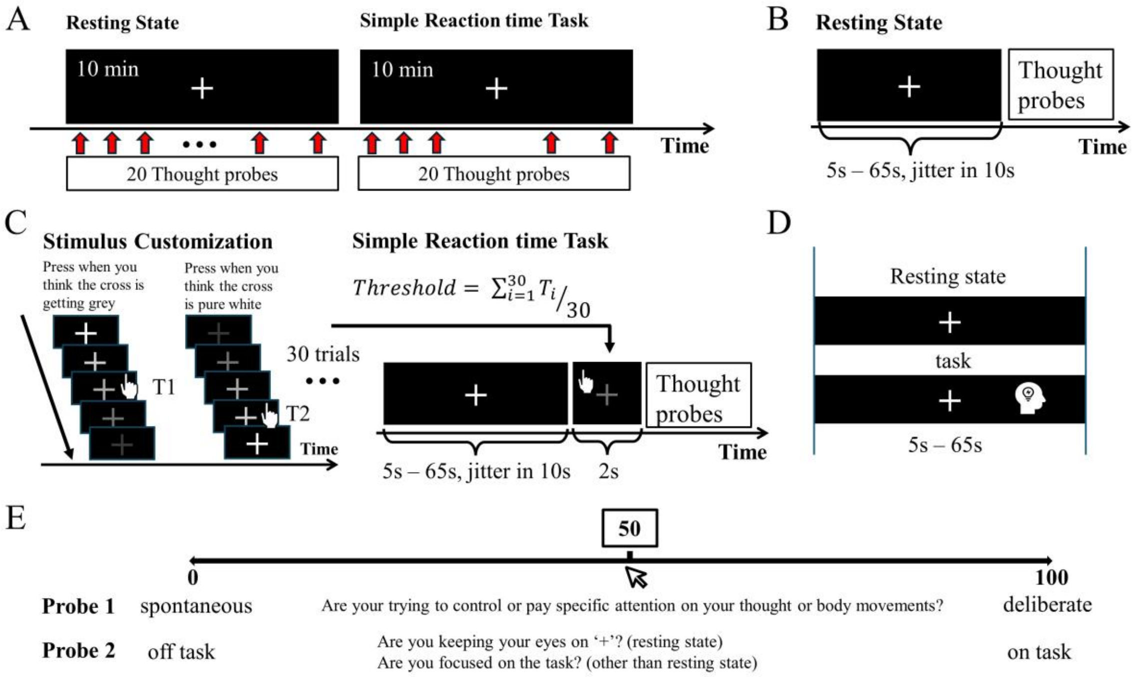


Figure 2. Experiment paradigm. **A. Overall experimental design.** The procedure comprised two tasks: a resting state and a simple reaction time task (RTT task), both of which lasted 10 minutes, where 20 thought probes were presented. **B. Resting state**. Participants were instructed to focus on the fixation cross and remain relaxed. They were also prompted to respond to thought probes at random intervals (ranging from 5s to 65s, with jitters of 10s). **C. Reaction time task (RTT task).** Prior to the task, participants' thresholds for identifying 'white' and 'grey' were determined. In the main part of the task, participants were asked to maintain their focus on the fixation cross, similar to the resting state, with one exception: upon detecting the fixation cross turning grey, they were required to press the space bar with their left hand as quickly as possible. The fixation cross remained for 2s regardless of whether a response was made. The duration before the fixation cross changed was randomized between 5s and 65s with jitters of 10s. Following the 2s response window, thought probes were presented. **D. Difference between pre-probe period in resting state and pre-stim period in RTT task.** The inter-probe interval (IPI) during resting state and inter-trial interval (ITI) during RTT share the same time length, so the only difference is that in the

RTT pre-stim period, participants need to prepare on both thought and body for the task response.
E. Thought probes. Participants were asked to evaluate the score of deliberate control, task relatedness using a visual analogue scale ranging from 0 to 100.

EEG recording and preprocessing

EEG data were collected using a 64-channel BrainAmp amplifier (Brain Products, Munich, Germany, international 10-20 system) at a sampling rate of 500 Hz. Fpz was used as the online reference, and Afz as the ground. The impedance for all electrodes was maintained below 5 kΩ. EEG preprocessing was conducted using the EEGLAB toolbox (Delorme & Makeig, 2004) (http://sccn.ucsd.edu/eeglab/). EEG signals were re-referenced offline to the average of all electrodes. The signals were band-pass filtered between 1 and 50 Hz using a zero-phase finite impulse response (FIR) filter implemented in EEGLAB (Delorme & Makeig, 2004). Filtering was performed using EEGLAB's default FIR filtering routine (pop_eegfiltnew), which applies a Hamming-windowed sinc FIR filter. The filter was applied in a two-pass (forward and backward) manner to achieve zero-phase distortion. Filter order was automatically determined by EEGLAB based on the transition bandwidth and sampling rate, following the heuristic implemented in pop_eegfiltnew, which aims to balance frequency resolution and temporal precision. This approach ensures adequate attenuation outside the passband while minimizing ringing artifacts. Bad channels were identified and removed using the clean_rawdata EEGLAB plugin with default parameters. All stationary artifacts, especially eye movements (blinks and saccades), were removed using Independent Component Analysis (ICA) and excluded using the MARA EEGLAB extension (Winkler et al., 2011, 2014). Data quality was visually verified to ensure that all signals included in subsequent analyses were of good quality and artifact-free. Preprocessing procedures (channel cleaning and ICA component removal) did not induce systematic between-participant differences in the number of usable RTT trials. We verified that usable trial counts did not differ across participants and that all reported ITPC effects were unchanged when statistically controlling for per-subject trial count.

EEG measurements

For EEG analysis, given that the shortest ITI was 5 seconds, in order to avoid edge effects caused by filtering operations, signals were first epoched into 6s before thought probes (-6s to 1000ms) for the resting state and from 6s pre-stim to 6s post-stim (-6s to 6s) for the RTT. The pre-stimulus period was taken as -4000 to 0s.

Peak frequency sliding

Peak frequency sliding (FS) quantifies the speed of changes in the instantaneous phase angle of a particular frequency range (e.g., alpha) of a neural oscillation over time, where higher FS indicates faster changes in oscillatory activity, and lower FS reflects slower changes in oscillations (Cohen, 2014b). Both computational modeling and human EEG studies have shown that increases in alpha FS (Cohen, 2014b; Hua et al., 2022; Mierau et al., 2017) are directly related to increased input to a neural network. For example, the strength of alpha FS can track the strength of visual input (Cohen, 2014b). These findings suggest that higher cognitive loads during task-focused thoughts are linked to increased alpha FS, making it a suitable measure for tracking the deliberate control and dynamics of on-task thoughts (Cohen, 2014b; Hua et al., 2022; Wolff, de la Salle, et al., 2019). Therefore, in this study, we focused on alpha (8–12 Hz) FS (Cohen, 2014b; Mierau et al., 2017; Rodriguez-Larios & Alaerts, 2019; Wolinski et al., 2018). Electrode Fz was selected for FS analysis to be consistent with previous literature (Hua et al., 2022). FS was computed following the method proposed by Cohen (2014b). The preprocessed data were first FIR bandpass filtered with 15% transition zone added to each edge of the filter range by applying the same FIR filter implemented in EEGLAB, then a Hilbert transform was done, after which the phase angle timeseries was extracted. FS is the first derivative of the phase angle timeseries and a median filter with a window size of 10 timepoints was applied in order to reduce non-physiological noise (Cohen, 2014b). Finally, the mean FS value during the pre-stimulus period (-4000ms to 0ms) was calculated.

Peak alpha frequency

Since FS is derived from the temporal derivative of the phase time series, we conducted a complementary control analysis using an alternative peak frequency estimate based on power rather than phase: peak alpha frequency (PAF) (Ramsay et al., 2021; Rathee et al., 2020). To estimate trial-level PAF, we extracted pre-stimulus EEG data (−4000 to 0 ms relative to stimulus onset) from the Fz electrode. The data were firstly linearly detrended before spectral analysis. Power spectral density (PSD) was computed for each trial using Welch's method with a 2-s Hamming window, 50% overlap, and zero-padding to the next power of two. The resulting spectra were averaged across the window segments to obtain a stable PSD estimate for each trial.

For each participant and trial, PAF was defined as the frequency with the maximum PSD within the alpha band (8–12 Hz) (Ramsay et al., 2021; Rathee et al., 2020). This procedure yielded a single PAF value per trial, which was stored for subsequent statistical analysis.

Sample entropy

While FS characterizes the speed of oscillatory dynamics, it does not quantify the predictability or uncertainty of neural signals over time. Sample entropy (SE) was therefore used as a complementary measure to capture the degree of temporal uncertainty in ongoing neural activity. SE is particularly well suited for assessing how ongoing thought states shape the predictability of future neural states, a property that is critical for understanding the influence of pre-stimulus dynamics on subsequent cognition and behavior. SE quantifies the degree of uncertainty and predictability of a time series from one time point to the next (Lau et al., 2022). A high SE value reflects high uncertainty, indicating that the next time point in the series is difficult to predict based on previous time points. Conversely, a low SE value denotes low uncertainty, suggesting that the next time point can be more easily predicted from preceding data. This study focuses on SE due to its established relationship with information input, as suggested in previous literature (Lau et al., 2022; Lechner & Northoff, 2023; Liu et al., 2018). Greater information input leads to increased complexity in neural oscillations, resulting in higher SE values (Lau et al., 2022; Lechner & Northoff, 2023; Liu et al., 2018). Furthermore, SE serves as a forward-looking metric, reflecting the extent to which the next time point in a series can be predicted. This property makes SE particularly relevant for examining how ongoing thoughts influence post-stimulus cognition and behavior (Lechner & Northoff, 2023; Liu et al., 2018). SE was computed for the alpha band (8–12Hz) during the pre-stimulus period (-4000ms to 0ms).

For a time series $\{x_i\}$, with embedding dimension m, tolerance *r*, and number of data points *N*, the sample entropy SE(m, r, N) is defined as the negative natural logarithm of the conditional probability that, given two sequences of length *m* with a distance less than *r*, the corresponding sequences of length *m+1* will also remain within distance *r*. The specific calculation procedure of sample entropy is as follows:

1. Construct an m-dimensional vector from the sequence$\{X(i)\}$, that is:

$$X(i) = [x(i), x(i+1), \cdots, x(i+m-1)], i = 1 \sim N-m+1$$

2. Define the distance between X(i) and X(j) as the maximum absolute difference of their corresponding elements:

$$X(i) = [x(i), x(i+1), \cdots, x(i+m-1)], \quad i = 1 \sim N-m+1$$

If the maximum absolute difference of the corresponding elements of X(i) and X(j) is less than r, then for each i, compute the distance between X(i) and all other vectors X(j), $j = 1,2, \cdots, N-m+1$.

3. For a given threshold r>0, count the number of times that

$$d[X(i), X(j)] < r$$

holds, and calculate the ratio of this number to the total number of vectors $N-m$. Denote it as

$$C_i^m(r) = \frac{1}{N-m} \operatorname{num}\{d[X(i), X(j)] < r\}, \quad i = 1,2, \cdots, N-m+1,\ i \neq j$$

4. Take the average over all i, denoted as $B^m(r)$:

$$B^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} B_i^m(r)$$

5. Increase the embedding dimension by one (m+1), and repeat steps 1)–4) to obtain $B_i^{m+1}(r)$ and $B^m(r)$.

6. Theoretically, the sample entropy of the sequence is then defined as:

$$SampEn(m, r) = \lim_{N \to \infty} \left\{ -\ln \frac{B^{m+1}(r)}{B^m(r)} \right\}$$

However, in practical applications N is finite. When N takes a limited value, the sample entropy is estimated as:

$$SampEn(m, r, N) = -\ln \frac{B^{m+1}(r)}{B^m(r)}$$

Following previous research (Lechner & Northoff, 2023), the embedding dimension (m) was set to 2, indicating that two consecutive data points were utilized for pattern matching. The similarity criterion (r) was established at 0.2, signifying that data points were deemed a 'match' (i.e., indistinguishable) if the absolute amplitude difference between them fell below 20% of the standard deviation of the time series.

Inter-trial phase coherence

To link pre-stimulus neural uncertainty with post-stimulus processing reliability, we quantified inter-trial phase coherence (ITPC). Inter-trial phase coherence (ITPC) quantifies the degree of phase consistency across trials for each participant (Cohen, 2014a; Duprez et al., 2021; López et al., 2019; Rapela et al., 2018; Van Diepen & Mazaheri, 2018). Whereas sample entropy (SE) captures the degree of temporal uncertainty within a single trial during the pre-stimulus period, ITPC indexes the consistency of phase alignment across trials following stimulus onset. Thus, SE and ITPC quantify complementary aspects of neural dynamics at different temporal and statistical levels: SE reflects how predictable neural activity is over time within a trial, while ITPC reflects how reliably neural responses are aligned across repeated events. This distinction allows us to test how greater pre-stimulus neural uncertainty translates into post-stimulus phase consistency and, in turn, behavioral responses.

ITPC is quantified as the length of the average phase vector across trials:

$$ITPC_{tf} = \left| \frac{1}{n} \sum_{r=1}^{n} e^{ik_{rf}} \right|$$

where n is the number of trials and $e^{ik_{rf}}$provides the complex polar representation of the phase angle k at time–frequency point *tf* on trial *r*. The double bars denote the vector length, reflecting the consistency of phase alignment across trials.

In this study, ITPC was computed for the period from -4000ms to 2000ms relative to stimulus onset during the RTT task. The ITPC values from -4000ms to -1000ms served as the baseline, and baseline correction was applied. Subsequently, the average baseline-corrected ITPC value for the post-stimulus period (0 to 1000ms) was calculated for each participant and used in further analyses. ITPC in the alpha band (8–12Hz) during the post-stimulus period (0 to 1000ms) was analyzed at electrode Fz. Additionally, ITPC in the theta (4–7Hz) and delta (1–4Hz) bands were analyzed as control conditions. Though some researches take theta/beta ratio as a marker of spontaneous thought (van Son, De Blasio, et al., 2019; van Son, de Rover, et al., 2019), some studies take such effect as an artifact caused by the changes of theta and alpha FS (Lansbergen et al., 2011) . Therefore, in this study we mainly focused on the frequency bands below beta and didn't take beta into consideration.

For participant-level analyses that used all available RTT trials per participant (target n=20), we computed baseline-corrected ITPC in the alpha band (8–12 Hz) over 0–1000 ms and used these ITPC values directly. For within-participant comparisons following the median split, each bin comprised exactly 10 trials. To equate for small and fixed n, ITPC was converted to ITPCz using the standard transformation with n=10.

Phase shuffling

To test whether FS and SE during the pre-stimulus period on post-stimulus neural oscillations and associated RT were mediated by phase characteristics, we performed phase shuffling on the EEG time series. This method randomizes the phase of the EEG signals without altering their amplitude (Lechner & Northoff, 2023).

After phase shuffling, the EEG signals were filtered into the alpha band (FIR filtering), and we re-evaluated pre-stimulus FS, pre-stimulus SE, and post-stimulus ITPC (see **Supplementary Figure 1** for FS and ITPC timeseries after phase shuffling) across different thought conditions (spontaneous vs. deliberate, off-task vs. on-task). Additionally, we calculated Pearson correlations between pre-stimulus SE and post-stimulus ITPC, pre-stimulus SE and reaction times as measured by RT, as well as post-stimulus ITPC and RT. If the observed effects of thought on neural oscillations, and the relationships between pre-stimulus and post-stimulus measures are genuinely phase-dependent, all significant effects should disappear after phase is shuffled (i.e., randomized).

Simulation

To examine whether sample entropy (SE) and frequency sliding (FS) are inherently coupled or dissociable, we performed a numerical simulation using synthetic signals with and without scale-free noise.

Pure sinewave condition. We first generated artificial signals consisting of a single pure sinewave. The signal length was fixed at 10 s, with a sampling rate of 500 Hz, yielding a time vector of 0–10 s in 1/500 s steps. Test frequencies ranged from 8 Hz to 20 Hz in 1-Hz increments. For each frequency, a sinusoidal signal was constructed as:

$$x(t) = sin(2\pi f t)$$

where f denotes the test frequency. In some cases, a small Gaussian noise (amplitude = 0.01) was added to evaluate robustness. Sample entropy (SE) was computed for each simulated signal using an embedding dimension $m = 2$ and a tolerance parameter $r = 0.2$ (defined as 20% of the signal's standard deviation). The last SE value was taken as the representative entropy for that frequency.

Sinewave with 1/f noise condition. In a second step, we extended the simulation to more realistic, scale-free signals by adding pink (1/f) noise. Pink noise was generated in the frequency domain (spectral exponent $\alpha = 1$), normalized to unit standard deviation, and scaled to a fixed amplitude of 0.3. Each sinewave (8–20 Hz, 10 s duration, 500 Hz sampling) was superimposed with the pink noise, yielding

$$x(t) = sin(2\pi f t) + \text{pink}(t)$$

The same SE parameters were applied ($m = 2$, $r = 0.2$), and SE was extracted for each frequency.

Statistical analysis

Median split

To perform statistical comparisons between thought types, a median split was applied to each participant's thought probe scores. The top 10 trials with the highest scores were classified as deliberate or on-task trials, while the bottom 10 trials were categorized as spontaneous or off-task trials. We then compared RT, pre-stimulus SE, pre-stimulus FS, pre-stimulus PAF, and post-stimulus ITPC between on-task and off-task as well as deliberate and spontaneous thoughts using paired T-tests. For ITPC comparisons, since each group contained 10 trials after the median split, we transformed ITPC values into ITPCz values using the following formula: $ITPCz = n * ITPC^2$, where *n* represents the number of trials (Cohen, 2014a).

Comparison between thought dimensions

To comprehensively characterize the relationship between task-relatedness and deliberate control, multiple complementary analyses were employed. Correlational, distributional, and categorical approaches were combined to assess not only the degree of association between the two dimensions, but also whether they differ in their distributional properties and trial composition across participants. First, we calculated the Pearson correlation between the visual analog scale (VAS) scores of the two dimensions on both a subject and trial basis (excluding outliers exceeding three standard deviations). Second, we applied the Kolmogorov-Smirnov (K-S) test to determine whether the distributions of the two thought dimensions across all trials were significantly different. Third, using the previously described median split, we calculated the number of trials for each participant that fell into the following four categories: (1) on-task and spontaneous, (2) off-task and spontaneous, (3) on-task and deliberate, and (4) off-task and deliberate. Since the counts of these four categories are categorical rather than continuous variables, we employed the non-parametric Friedman test to assess whether there were significant differences among the counts.

If the two dimensions exhibit high similarity, we would expect a strong correlation between their VAS scores and no significant difference between their distributions. Additionally, the number of on-task and deliberate trials would be significantly greater than the number of on-task and spontaneous trials, while the number of off-task and spontaneous trials would be significantly greater than the number of off-task and deliberate trials.

Mediation model

We employed a mediation model to examine the relationship between thought, pre-stimulus FS, and SE. This analysis was conducted at the trial level, meaning all trials across all participants were included in the model. This approach was chosen under the assumption that thoughts vary across trials, and a subject-level analysis, which captures inter-subject variability, would obscure the trial-specific impact of thoughts on the measured variables. In this model, thought VAS scores were included as the independent variable, FS as the mediator, and SE as the dependent variable. We chose FS—rather than SE—as the mediator because SE quantifies whether originally similar patterns remain similar after the addition of one more time point, thereby capturing the uncertainty introduced by a single time point. Crucially, this uncertainty is inherently frequency-dependent: at higher frequencies, the addition of a single time point introduces greater uncertainty. From this perspective, positioning FS as the mediator is mathematically well justified. In addition, we used a mediation model to investigate how pre-stimulus SE influences post-stimulus reaction time (RT) through post-stimulus ITPC as a mediator. For this analysis, a subject-level approach was adopted, as ITPC measures phase coherence across all trials for each participant.

The mediation analysis was implemented using the PROCESS macro for SPSS (version 4.1) (Hayes, 2012), employing Model 4, which specifies a simple mediation structure. Indirect effects were estimated using a nonparametric bootstrapping procedure with 5,000 resamples, and 95% bias-corrected confidence intervals were computed. An indirect effect was considered statistically significant when the confidence interval did not include zero. All variables were entered in their original continuous form.

Given that the pre-stimulus (Thought → FS → SE) and post-stimulus (SE → ITPC → RT) pathways were analyzed at different hierarchical levels, we additionally applied both single-level and multilevel structural equation modeling (SEM) approaches to more comprehensively assess the mediation effects along the pre-stimulus Thought–FS–SE pathway.

In the single-level models, mediation was examined exclusively at the trial level (within-subject), treating trials as independent observations while clustering standard errors by subject. These models specified that the experimental condition (Deliberate Control or Task-Relatedness) predicted the first-stage mediator (FS), which in turn predicted the second-stage mediator (SE). The condition also had a direct effect on SE, allowing for the estimation of both direct and indirect effects. Standard errors were estimated using nonparametric bootstrapping with 2000 resamples to derive confidence intervals for indirect and total effects.

In the multilevel models, we explicitly modeled two levels of data: the trial level (Level 1) and the subject level (Level 2). The Level 1 structure mirrored that of the single-level model, capturing within-subject variability. At Level 2, the same mediation paths were modeled across subjects, allowing us to decompose between-subject effects. This hierarchical approach permitted the estimation of cross-level mediation (e.g., whether the effect of Deliberate Control or Task-Relatedness on FS and SE varied across individuals). These models were estimated using robust Huber-White sandwich estimators to account for non-independence within subjects.

Separate models were estimated for each experimental condition (Deliberate Control and Task-Relatedness) using the lavaan package in R. All models treated Subject as the clustering variable. Final results report standardized path coefficients and 95% confidence intervals for direct, indirect, and total effects at each level.

Resting state analysis

To verify that the relationship between thoughts and pre-stimulus oscillations (FS and SE) were truly task-related and not an artifact of thought processes during the resting state, we selected 4000 ms (matching the pre-stimulus period in the task) prior to each thought probe in the resting state as pseudo-trials and calculated FS and SE for these pseudo-trials. By constructing pseudo-trials matched in duration to the task pre-stimulus window, this analysis allows us to determine whether similar thought-related neural differences are present in the absence of task demands. As in the task condition, we applied a median split on thought VAS scores for each participant to divide trials into spontaneous and deliberate trials (based on deliberate control) and off-task and on-task trials (based on task relatedness). Paired T-tests were then conducted to compare FS and SE between spontaneous and deliberate trials, as well as between off-task and on-task trials in these pseudo-trials.

Results

Both thought dimensions (deliberate control and task relatedness) shape task-related behavior (RT) and are closely related to one another

The nature of thought impacts behavioral performance during cognitive tasks (e.g., RT) (Bastian & Sackur, 2013; Franklin et al., 2011; Smallwood et al., 2008; Smallwood & Schooler, 2006). Here, we tested whether the thought dimensions, deliberate control, and, task relatedness are important determinants of performance. We first employed paired t-tests to examine whether RT during the RTT task differed between spontaneous and deliberate thoughts, as well as between off-task and on-task thoughts. RT during deliberate thoughts was significantly shorter than during spontaneous thoughts ($t(39) = 3.47$, $p = 0.001$; **Figure 3A**). Likewise, RT during on-task thoughts was shorter as compared to off-task thoughts ($t(39) = 3.69$, $p = 0.001$; **Figure 3B**). This pattern of results raises the question of whether the thought dimensions of task relatedness and deliberate control are linked to one another. To address this, we first applied Pearson correlation analysis to the VAS scores of these two dimensions at both the subject-level (averaging VAS values for each participant before correlation) and the trial-based (correlating all trials across all participants). Results revealed that task relatedness (on-task vs. off-task) was highly correlated with deliberate control (spontaneous vs. deliberate) at both levels (subject-level: $r(38) = 0.80$, $p < 0.001$, **Figure 3C**; trial-based: $r(798) = 0.71$, $p < 0.001$, **Figure 3D**).

Furthermore, we conducted a two-sample Kolmogorov-Smirnov (K-S) test to compare the distributions of both task relatedness and deliberate control across all trials. The results showed no significant difference between the distributions of these two thought dimensions ($D = 0.06$, $p = 0.178$, **Figure 3E**), indicating no significant difference in terms of their distributions. This further confirms the close relationship between the two thought dimensions.

Finally, we calculated the number of trials for each participant that fell into the following four combinations: (1) spontaneous and on-task, (2) spontaneous and off-task, (3) deliberate and on-task, and, (4) deliberate and off-task. We then tested whether the counts differed significantly using a non-parametric Friedman test. Results indicated significant differences among the four groups (p<0.001, **Figure 3F**). Post-hoc comparisons with Dunn’s multiple comparisons test revealed that the trial numbers of spontaneous/off-task and spontaneous/on-task thoughts differed significantly as did spontaneous/off-task and deliberate/off-task thoughts (all p < 0.001, **Figure 3F**). These results indicate an association of spontaneous thoughts with off-task thoughts than with on-task thoughts, whereas deliberate thoughts are more linked to on-task thoughts than off-task thoughts. In contrast, spontaneous/off-task and deliberate/on-task thoughts were statistically indistinguishable (all p > 0.999, **Figure 3F**); this suggests a close relationship between the two thought dimensions at their extreme ends.

In conclusion, these behavioral findings suggest that the thought dimensions of deliberate control and task relatedness are both associated with task-related behavior, namely RT. More deliberate and on-task thoughts are linked to shorter RTs, whereas spontaneous and off-task thoughts are associated with longer RTs. Thus highlighting their interrelatedness. This close association was further substantiated by the observation that spontaneous thoughts were more strongly associated with off-task thoughts, while deliberate thoughts were more closely linked to on-task thoughts. Therefore, at the behavioural level, the two thought dimensions are closely coupled with each other.

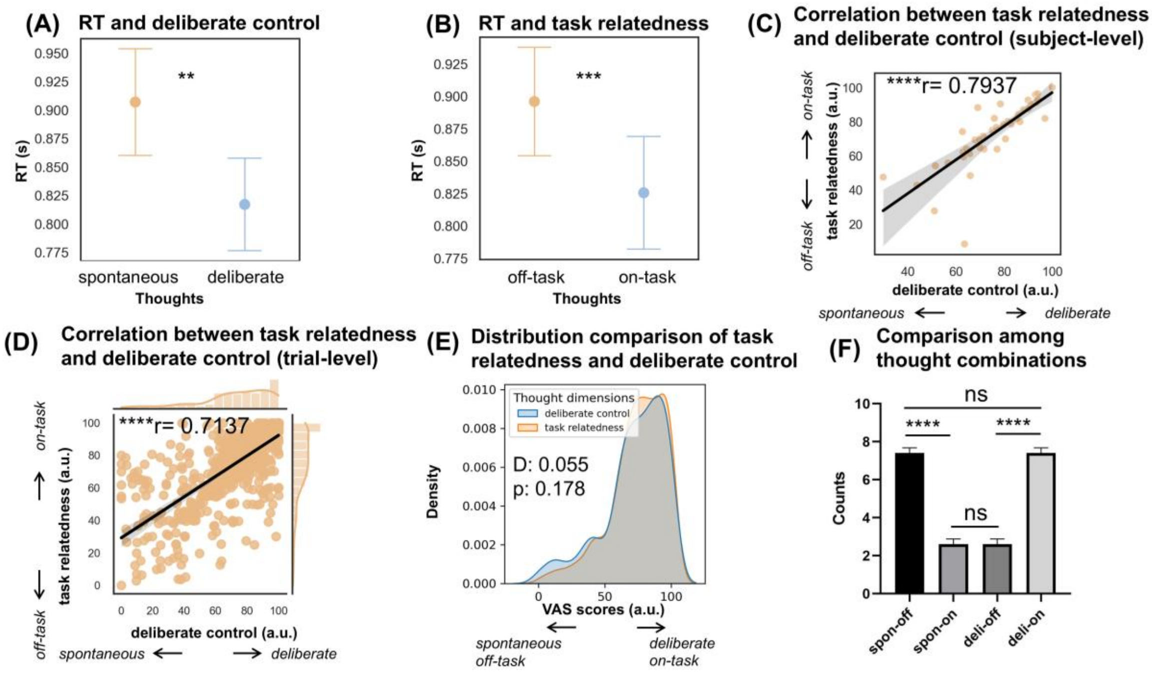


Figure 3. Behavioral analysis of reaction times (RT) and thought dimensions. (A) RTs and deliberate control. RTs were significantly shorter during deliberate thoughts compared to spontaneous thoughts. **(B) RTs and task relatedness.** RTs were significantly shorter during on-task thoughts compared to off-task thoughts. **(C) Correlation between task relatedness and deliberate control (subject-level).** Task relatedness and deliberate control showed a strong positive correlation at the subject level. **(D) Correlation between task relatedness and deliberate control (trial-level).** Task relatedness and deliberate control were also strongly

correlated at the trial level. **(E) Distribution comparison of task relatedness and deliberate control.** No significant differences were found between the distributions of these two dimensions across trials. **(F) Comparison among thought combinations.** The distribution of trials among the four thought combinations revealed significant differences, highlighting the predominant co-occurrence of on-task thoughts and deliberate, as well as of off-task thoughts with spontaneous. Note: *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$; ****: $p < 0.0001$; ns: not significant.

On-task and deliberate thought show faster and less predictable neural dynamics during pre-stimulus activity

In the previous section, we demonstrated the close relationship of the two thought dimensions (task relatedness and deliberate control) at the behavioral level. Does this also hold at the neuronal level? In that case, one would expect that these thought dimensions are also not dissociable in terms of relevant neural measures. Paired t-tests (**Figure 4B**) showed that pre-stimulus FS for spontaneous vs. deliberate control (t(39) = 2.28, p = 0.028), on- vs. off-task (t(39) = 2.29, p = 0.027) significantly differed, as did SE for spontaneous vs. deliberate control (t(39) = 2.83, p = 0.007) and on- vs. off-task (t(39) = 3.191, p = 0.0028).

Given their similar direction with respect to the two thought dimensions, we next correlated pre-stimulus FS with SE. As expected, Pearson correlation analysis revealed that FS and SE were significantly correlated during the pre-stimulus period (r(37) = 0.49, p = 0.002; **Figure 4C**). Given previous literature showing that changes of SE could be taken as consequence of FS (Aboy et al., 2007), we applied a mediation model to analyze the relationships among thought VAS scores, pre-stimulus FS, and pre-stimulus SE. The results indicated full mediation effects for both thought dimensions (deliberate control: a = 0.079, p = 0.025, b = 0.350, p < 0.001, c' = 0.048, p = 0.148, c = 0.076, p = 0.032, indirect effect = 0.028, Bootstrap CI = [0.0058, 0.0514]; task relatedness: a = 0.082, p = 0.020, b = 0.351, p < 0.001, c' = 0.034, p = 0.308, c = 0.063, p = 0.076, indirect effect = 0.029, Bootstrap CI = [0.0054, 0.0532]; **Figure 4D**). Moreover, no mediation effect can be found when thought dimensions were taken as mediators (deliberate control: a = 0.079, p = 0.025, b = 0.048, p = 0.148, c' = 0.350, p < 0.001, c = 0.354, p < 0.001, indirect effect = 0.004, Bootstrap CI = [-0.0014, 0.0115]; task relatedness: a = 0.082, p = 0.020, b = 0.034, p = 0.308, c' = 0.351, p < 0001, c = 0.354, p < 0.001, indirect effect = 0.004, Bootstrap CI = [-0.0014, 0.0115]; **Supplementary Figure 2**) or dependent variables (deliberate control: a = 0.354, p < 0.001, b = 0.055, p = 0.148, c' = 0.060, p = 0.112, c = 0.079, p = 0.025, indirect effect = 0.019, Bootstrap CI = [-0.0063, 0.0476]; task relatedness: a = 0.354, p < 0.001, b = 0.039, p = 0.308, c' = 0.069, p = 0.069, indirect effect = 0.014, Bootstrap CI = [-0.0105, 0.0405]; **Supplementary Figure 2**). Together, these findings suggest that the impact of both thought dimensions on pre-stimulus entropy is fully mediated by FS. Specifically, the neural impact of the two thought dimensions on uncertainty (SE) is mediated by the phase-based measurement of neural speed (FS).

To further validate this mechanistic relationship, we conducted a supplementary simulation using synthetic signals with and without scale-free noise (Supplementary Figure 3). When the signal consisted of a pure sinewave, increasing frequency did not lead to any systematic change in SE, indicating that SE and FS were independent for purely rhythmic dynamics (Supplementary Figure 3). However, when 1/f noise was added—approximating the broadband characteristics of real EEG—SE exhibited a clear upward trend with increasing frequency (Supplementary Figure 3). This pattern demonstrates that the coupling between FS and SE emerges only in the presence of scale-free background dynamics. Hence, the observed FS–SE relationship in EEG likely reflects the contribution of scale-free neural processes, which provide the background that enables oscillatory speed to change entropy (Ao et al., 2025).

Given that FS itself is phase-based (Cohen 2014), we tested for the impact of the phase-related processes on our pre-stimulus measures' relation with the two thought dimensions. To test whether the relationships between pre-stimulus FS and SE with the two thought dimensions are phase-dependent (rather than just amplitude-based), we conducted paired t-tests on phase-shuffled pre-stimulus FS and SE. Unlike when phase is un-shuffled, the results showed no significant differences between off-task and on-task thoughts or between spontaneous and deliberate thoughts after phase shuffling (all $p > 0.16$; **Supplementary Figure 4**). As an additional control analysis, we also employed an alternative method for estimating peak frequency based on power rather than phase, namely peak alpha frequency (PAF), and tested whether it differed across thought conditions. Paired t-tests revealed that this power-based measure showed no significant differences between thought states (deliberate control: $t(39) = 0.33$, $p_{fdr} = 1.000$; task-relatedness: $t(39) = 1.69$, $p_{fdr} = 1.000$). These findings suggest that the impact of both pre-stimulus FS and SE on the two thought dimensions is mediated by their underlying phase-related processes.

Are the observed relationships of pre-stimulus dynamics with the two thought dimensions associated with the task context in which they are set? To test for that, we conducted the same analyses, e.g., paired t-tests on FS and SE, in resting state pseudo-trials which has the same timing as in the pre-stimulus of task. To verify whether the relationship between thought and pre-stimulus FS and SE were task-related, we conducted paired t-tests on FS and SE in resting-state pseudo-trials. The results showed no significant differences in either FS or SE between spontaneous and deliberate thoughts or between off-task and on-task thoughts in resting state pseudo-trials (FS deliberate vs. spontaneous thought: $t(39) = 0.50$, $p = 0.618$; FS on-task vs. off-task: $t(39) = 0.14$, $p = 0.888$; SE deliberate vs. spontaneous: $t(39) = 0.63$, $p = 0.530$; SE on-task vs. off-task: $t(39) = 1.95$, $p = 0.058$, **Supplementary Figure 5**). This suggests that the relationship of the impact of the pre-stimulus dynamics on the two thought dimensions is associated with the task context as it does not occur during the absence of a task during the resting state.

Together, these findings suggest that both on-task and deliberate thoughts accelerate phase-based neural speed (FS) and, at the same time, increase the uncertainty/ flexibility (SE) of the neural oscillations during the pre-stimulus period. The supplementary simulation further demonstrates that this FS–SE coupling originates from scale-free neural dynamics, providing a mechanistic account for how different types of thought (on-task/deliberate vs. off-task/spontaneous) exert distinct influences on pre-stimulus neural activity.

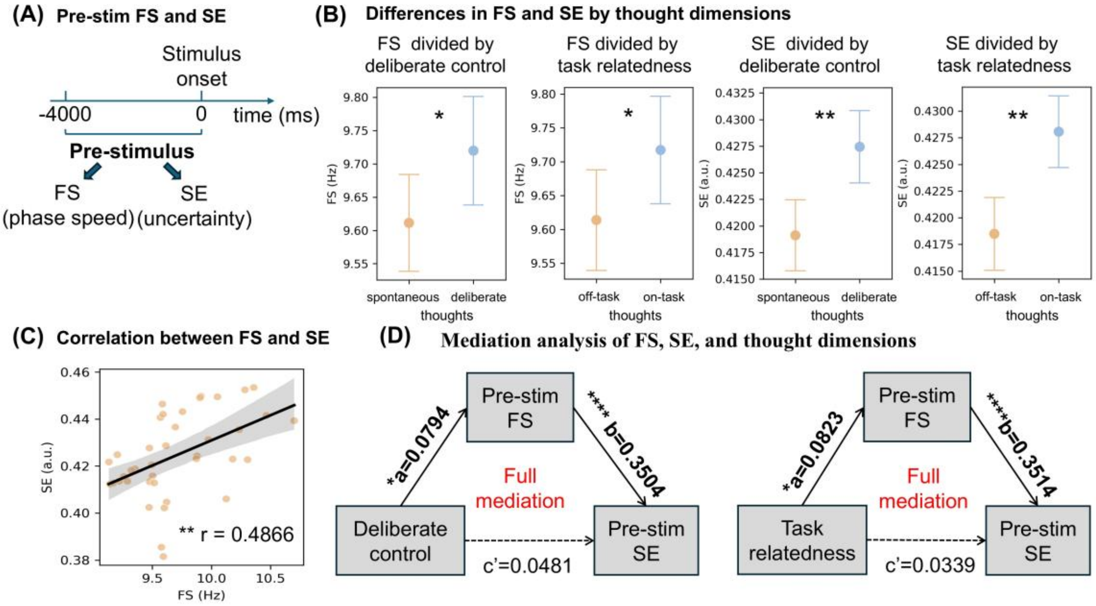


Figure 4. Pre-stimulus neuro-oscillations dynamics and their relationship with thought dimensions. (A) Pre-stimulus FS and SE. The average alpha-band (8–12Hz) FS and SE over the pre-stimulus period (-4000ms to 0ms) was calculated to examine neural oscillations preceding stimulus onset. **(B) Differences in FS and SE by thought dimensions.** Both pre-stimulus FS and SE were significantly higher during on-task and deliberate thoughts compared to off-task and spontaneous thoughts. **(C) Correlation between FS and SE.** A significant positive correlation was observed between pre-stimulus FS and SE in the alpha band, highlighting their interplay during the pre-stimulus period. **(D) Mediation analysis of FS, SE, and thought dimensions.** Mediation models revealed that pre-stimulus FS fully mediated the relationship between thought dimensions (deliberate control and task relatedness) and pre-stimulus SE, indicating a tight linkage between ongoing neuro-oscillation dynamics and ongoing thought. Note: *: $p < 0.05$; **: $p < 0.01$; ****: $p < 0.0001$; In the mediation models, solid lines indicate a significant effect, while dashed lines represent a non-significant effect.

To further examine the mechanistic role of FS in linking thought dimensions with pre-stimulus SE, we conducted mediation analyses separately for deliberate control and task-relatedness by applying SEM. In the single-level models with cluster-robust standard errors, both dimensions showed significant indirect effects on SE through FS. Deliberate control positively predicted FS ($a = 0.002$, $p = 0.013$), FS in turn predicted SE ($b = 0.022$, $p < 0.001$), while the direct effect of deliberate control on SE was not significant ($c' = 0.000$, $p = 0.160$). The indirect effect was significant ($p = 0.016$), yielding a significant total effect ($p = 0.036$). A highly similar pattern was observed for task relatedness: Probe2 positively predicted FS ($a = 0.003$, $p = 0.013$), FS predicted SE ($b = 0.022$, p <

0.001), while the direct path to SE was again not significant (c′ = 0.000, p = 0.273). The indirect effect reached significance (p = 0.016), and the total effect was marginally significant (p = 0.055). These results indicate that, at the trial level, both deliberate control and task relatedness influence SE indirectly through FS, with FS serving as a full mediator.

In contrast, multilevel mediation analyses that separated within- and between-subject variance did not yield significant indirect effects for either dimension (all p > 0.2). At both levels, the paths from deliberate control and task-relatedness to FS and SE were nonsignificant, while the paths from FS to SE remained robust (for both dimensions: within: b = 0.020, p < 0.001; between: B = 0.025, p < 0.001). This pattern suggests that the indirect effects detected in the single-level models largely reflect trial-level variability, whereas FS → SE constitutes the most consistent and reliable pathway across analytic levels.

Pre-stimulus SE affects RT mediated by post-stimulus ITPC

We show that both thought dimensions are related with task-related RT while, at the same time, being related to pre-stimulus activity neuro- dynamics, e.g., FS and SE. This raises the question whether and how the pre-stimulus dynamics affects post-stimulus RT. Given the randomized intervals between stimuli in our task paradigm, we propose that higher ITPC reflects a more consistent internal brain state, wherein participants are in a sustained on-task and deliberate mode, allowing neural oscillations to align optimally just before stimulus onset. Therefore, we calculated phase-based intertrial phase coherence (ITPC) in alpha band (8–12Hz) for the period 0–1000ms (See **Figure 5A & 5B**). First, we applied Pearson correlation analysis between post-stimulus ITPC and RT. The results showed a significant correlation (r(36) = -0.38, p = 0.018; **Figure 5C**): the higher ITPC in the alpha band, the shorter RT. As a control, we also calculated Pearson correlations between post-stimulus ITPC in the delta (1–4Hz) and theta (4–7Hz) bands with RT, neither of which showed significant correlations (delta: r(37) = -0.18, p = 0.293; theta: r(37) = -0.28, p = 0.085; **Supplementary Figure 6**). Furthermore, although ITPC was related to RT, it did not differ across either thought dimension when using median splits and ITPCz (deliberate control: t(39) = 1.18, p = 0.245; task relatedness: t(39) = 1.53, p = 0.134, **Supplementary Figure 7**). This outcome raises an important question regarding how pre-stimulus neuro-dynamics influence the subsequent post-stimulus period in both its neural and behavioral measures.

To test whether pre-stimulus neuro-dynamics affect post-stimulus RT, we calculated the Pearson correlation between pre-stimulus SE and RT. The results show a significant correlation (r(37) = -0.36, p = 0.027; **Figure 5D**), whereby higher pre-stimulus SE was associated with shorter RT in the post-stimulus period. Moreover, pre-stimulus SE was also significantly correlated with post-stimulus ITPC (r(39) = 0.34, p = 0.034; **Figure 5E**), whereby higher pre-stimulus entropy was associated with higher post-stimulus ITPC.

As a control, we also calculated Pearson correlations on phase-shuffled data between post-stimulus alpha ITPC and RT, pre-stimulus SE and post-stimulus ITPC, as well as pre-stimulus SE and RT. The results showed no longer any significant correlations (all $p > 0.3$; **Supplementary Figure 8**). This suggests the key relevance of phase-based processes for connecting pre-stimulus dynamics with post-stimulus coherence and behavior.

To further specify the pre-post-stimulus relationships, we applied a mediation model among pre-stimulus SE, post-stimulus ITPC, and RT. The results showed a significant full mediation effect (a = 0.336, p = 0.034, b = -0.315, p = 0.045, c’ = -0.292, p = 0.061, c = -0.398, p = 0.011, indirect effect = -0.106, Bootstrap CI = [-0.2286, -0.0074]; **Figure 5F**). The impact of pre-stimulus neural dynamics (SE), on post-stimulus behavior (RT), is fully mediated by the degree of phase coherence (ITPC) at stimulus onset. In contrast to SE, no such mediation model was observed for pre-stimulus FS (a = 0.185, p = 0.254, b = -0.431, p = 0.007, c’ = 0.098, p = 0.523, c = 0.018, p = 0.912, indirect effect = -0.0800, Bootstrap CI = [-0.2587, 0.0371]; **Supplementary Figure 9**). This suggests a key role for SE (but not for FS) in directly connecting pre- and post-stimulus activity.

Finally, we applied mediation models among pre-stimulus SE and FS with post-stimulus ITPC and RT respectively on phase shuffled data, results show no mediation effect was found (SE: a = -0.013, p = 0.935, b = -0.006, p = 0.973, c’ = 0.057, p = 0.731, c = 0.057, p = 0.727, indirect effect = 0.000, Bootstrap CI = [-0.0730, 0.0930]; FS: a = 0.077, p = 0.637, b = -0.006, p = 0.971, c’ = -0.004, p = 0.983, c = -0.004, p = 0.981, indirect effect = -0.005, Bootstrap CI = [-0.1068, 0.0870]; **Supplementary Figure 10**).

Together, the findings show a key role for phase-based processes in mediating the impact of pre-stimulus dynamics on post-stimulus activity and behavior. Specifically, pre-stimulus entropy is associated with post-stimulus reaction time through the phase-based ITPC. These results suggest that the impact of task-relatedness and executive control on task-related neural activity and its behavior is mediated by their impact on pre-stimulus phase-based neural dynamics (FS, SE). In addition, through phase-based ITPC, this is carried over to the subsequent post-stimulus period.

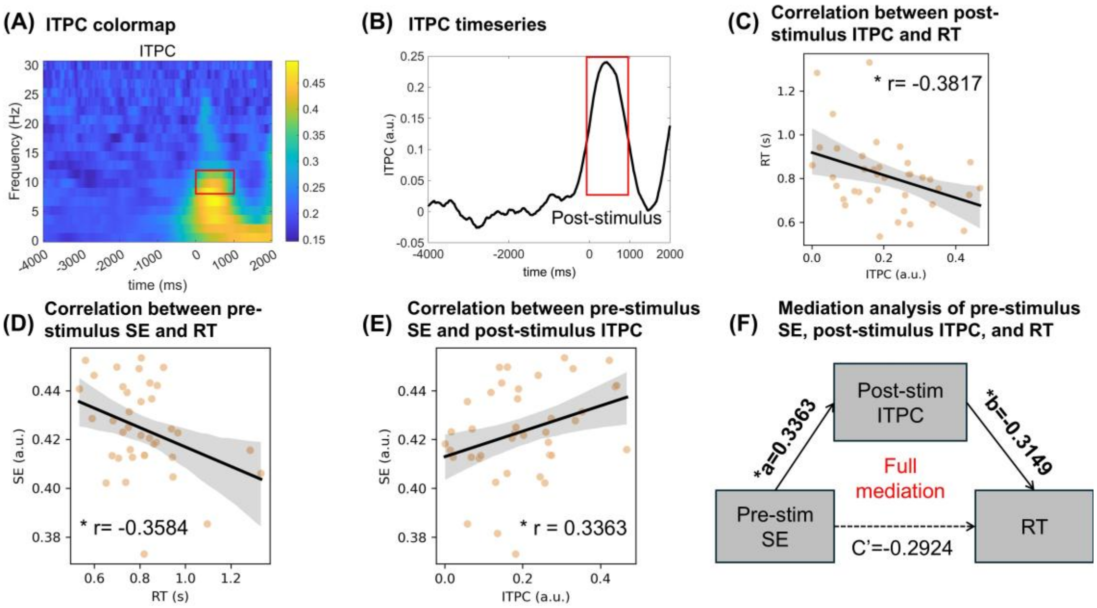


Figure 5. Relationships between on-going thought and neural activity, post-stimulus neural activity, and response time (RT). (A, B) Post-stimulus ITPC in the alpha band. Post-stimulus ITPC in the alpha band (8–12 Hz) was calculated for the 0–1000ms period to assess neural coherence following stimulus onset. **(C) Correlation between post-stimulus ITPC and RT.** A significant negative correlation was observed, indicating that higher post-stimulus ITPC is associated with faster RTs. **(D) Correlation between pre-stimulus SE and RT.** Pre-stimulus SE in the alpha band was significantly negatively correlated with RT, suggesting that pre-stimulus neural oscillations influence response speed. **(E) Correlation between pre-stimulus SE and post-stimulus ITPC.** Pre-stimulus SE was significantly positively correlated with post-stimulus ITPC, linking pre-stimulus dynamics to post-stimulus neural activity. **(F) Mediation analysis of pre-stimulus SE, post-stimulus ITPC, and RT.** A mediation model revealed that post-stimulus ITPC significantly mediated the relationship between pre-stimulus SE and RT, demonstrating that pre-stimulus neuro-oscillation dynamics influence response speed via post-stimulus neural synchronization (ITPC). Note: *: $p < 0.05$; ns: not significant.

Decoupling of Thought Dimensions during the resting state abolishes their differential association with neuro-dynamics

We demonstrate clear differences in the pre-stimulus neuro-oscillation dynamics between on-task deliberate and off-task spontaneous thoughts. This raises the question of where and how such differences originate. This raises the question whether prediction/anticipation plays a key role in differentiating on-task deliberate and off-task spontaneous thoughts in their pre-stimulus neuro-oscillation dynamics. While we did not include direct measures of prediction/anticipation in our design, we can nevertheless address this question in an indirect way, namely though comparing task state with the resting state.

Paired t-tests were conducted to examine differences in two thought dimensions (measured by VAS) between the resting state and task conditions. The results showed that deliberate control scores were significantly lower in the resting state than during the task condition (t(39) = 2.98, $p_{fdr} = 0.010$; **Figure 6A**). In contrast, there were no significant differences in task-relatedness scores between resting and task states (t(39) = 0.90, $p_{fdr} = 1.000$; **Figure 6B**).

Given the high correlation between the two dimensions (deliberate control and task relatedness) under the task condition, we also investigated their relationship during the resting state. Pearson correlations were computed separately for trials and individuals in the resting state, and the distributions of trials across the two dimensions were compared by applying K-S test. Despite a high correlation also observed during the resting state (subject-based: $r(38) = 0.73, p < 0.001$; trial-based: $r(798) = 0.57$, $p < 0.001$; **Supplementary Figure 11**), the distribution of the two thought dimensions were significantly distinct between each other during the resting state (but not during the task state; see above) (D = 0.13, $p < 0.001$; **Figure 6C**). We then compared the two thought dimensions' correlation coefficients between resting and task states: Pearson and Filon's *z*-test showed a significant difference in their correlation coefficients between task and resting state conditions with the latter being significantly lower than the former ($z = -5.11, p < 0.001$). To quantify the two thought dimensions' degree of decoupling during the resting state (compared to the task state), we calculated the absolute difference in their correlation coefficients as a measure of coupling strength; then we performed a permutation test (1000 iterations) to assess whether the observed difference was significantly greater than random noise. Results demonstrated that the task-resting state difference in their coupling strength between thought dimensions (as measured by the absolute value of correlation coefficients) was indeed significant (real difference = 0.113; permutation mean difference = -0.001, 95% CI [-0.0627, 0.0631]; $p = 0.001$; **Figure 6D**). These findings suggest a certain degree of decoupling between the two thought dimensions during the resting state compared to the task state.

Lastly, we investigated whether this decoupling affected the relationship between thought dimensions and pre-stimulus neuronal dynamics (FS and SE). During the resting state, no significant differences were observed in FS or SE across either dimension—deliberate control (FS: $t(39) = 0.50$, $p = 0.618$; SE: $t(39) = 0.63, p = 0.530$; **Figure 6E-F**) or task-relatedness (FS: $t(39) = 0.14, p = 0.888$; SE: $t(39) = 1.95$, $p = 0.058$; **Figures 6G-H**). Though tentative, these results indicate that the heightened FS (acceleration in phase-based speed) and SE (increase in uncertainty) occur only during the task condition with its tight coupling of the two thought dimensions (deliberate control and task-relatedness).

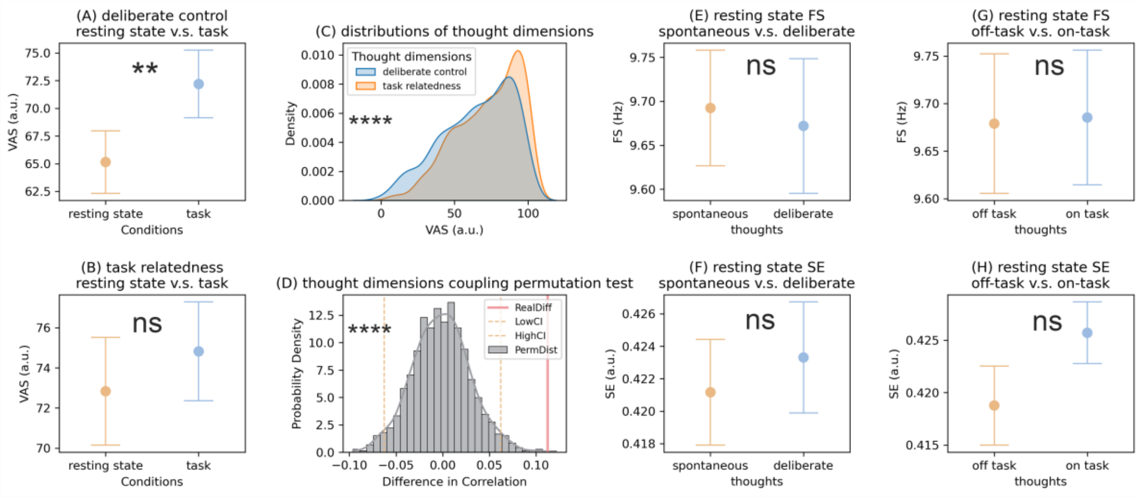


Figure 6. Reduced coupling between thought dimensions (deliberate control and task-relatedness) in the resting state and relationship to neuro-oscillation dynamics (FS and SE). (A) Comparison of deliberate control between task and resting state. Deliberate control ratings increase significantly during task, indicating greater intentional regulation of thoughts (more deliberate) when anticipating stimulus onset. **(B) Comparison of task relatedness between task and resting state.** Task-relatedness remains similar across resting state and task conditions, suggesting that the relevance of thoughts to an external goal does not change substantially. **(C) Distributions of the two thought dimensions are significantly different from each other during task and resting states.** Distributions of the two thought dimensions, deliberate control and task relatedness, differ significantly from each other in resting state, implying weaker coupling when participants are not preparing for a task. **(D) Reduced coupling between the two thought dimensions in resting state compared to task condition.** Comparing the two thought dimensions' correlation coefficients reveals a significant decrease in their correlation strength during the resting state compared to the task state, confirmed by a permutation test. **(E–H) No neuro-oscillation dynamical differences (FS and SE) among the thought dimensions at rest.** Neither FS nor SE shows significant changes across varying levels of deliberate control (E-F) and task-relatedness (G-H) in the resting state., suggesting heightened FS and SE only emerge when deliberate control and task-relatedness are tightly coupled, as in the task condition.

Discussion

This study explored how two thought dimensions: deliberate control and task relatedness, shape pre- and post-stimulus neuronal phase dynamics and task-related behavior. We found that during the pre-stimulus period, on-task and deliberate thoughts were associated with higher FS and SE, compared to off-task and spontaneous thoughts. This suggests that distinct types of thought are characterized by unique neuronal dynamic signatures in their phase and periodicity of the EEG signal. A mediation model revealed that FS fully mediated the effect of thought dimensions on SE, suggesting that neuro-oscillation speed (FS) drives neural uncertainty/flexibility (SE). Thus, the phase of the signal appears to be the important factor in understanding the relationship to the task-relatedness and spontaneity of thought processes.

Furthermore, we observed increased SE during the pre-stimulus period, which was associated with enhanced phase alignment at stimulus onset. This ultimately facilitated faster RT.

Although the resting state data emphasized that deliberate control and task-relatedness may constitute dissociable dimensions of thought, our task data showed that they were strongly coupled in a different context, e.g., task rather than rest. This suggests that under task demands, these two dimensions may converge onto a common underlying mechanism in externally constrained contexts (e.g., executive control engaged to sustain task focus), whereas their relationship may be rather loose in unconstrained contexts such as the resting state. This task–resting difference indicates that the dissociation of thought dimensions may be state- and context-dependent rather than universal, underscoring the importance of investigating the shared mechanisms that jointly shape both dimensions during task state.

Importantly, the absence of thought-related differences in pre-stimulus FS and SE during the resting state indicates that the observed thought–neural coupling is not a static trait-like property of individuals. Instead, it emerges specifically in the context of task preparation, when ongoing thought is embedded within an anticipatory behavioral framework. This state dependence suggests that task structure gates the expression of phase-based neural dynamics, enabling thought to be associated with pre-stimulus neural speed and uncertainty only when future action is required. In this sense, ongoing thought acquires behavioral relevance through its interaction with task-driven temporal expectations.

Together, our findings support the possibility of a sequential influence of thought on behavior via phase-based neural dynamics, but do not establish causality. Importantly, the phase shuffling analysis revealed that the phase state is the critical driver of these relationships, underscoring the central role of phase dynamics in linking thought over pre-stimulus dynamics to post-stimulus activity and the associated behavior. Crucially, the present findings also delineate a clear boundary between phase-based and power-based neural measures in relation to thought. Although pre-stimulus FS robustly differentiated thought dimensions, an alternative power-based estimate of peak alpha frequency (PAF) showed no reliable differences across deliberate versus spontaneous or on-task versus off-task states. This dissociation indicates that the neural signatures of thought are not captured by static spectral power or peak frequency per se, but rather by the temporal dynamics of phase evolution. Thus, the absence of PAF effects is theoretically informative, constraining the observed thought–neural relationships to phase-based mechanisms rather than amplitude- or power-driven processes.

The following sections provide further discussion about the meaning of these findings in terms of cognition and behaviour, and their underlying neuronal phase-related mechanisms.

From Thoughts to Pre-Stimulus Neural Dynamics: Mechanistic Insights

FS represents the speed of neural oscillation, reflecting the rate of change of phase over time (Cohen, 2014b; Hua et al., 2022). Particularly for the alpha band, faster FS enables the brain to more efficiently process input information (Cohen, 2014b; Hua et al., 2022; Mierau et al., 2017). On-task and deliberate thoughts are associated with higher FS, indexing faster neural speed, facilitating enhanced cognitive control and preparation for the incoming stimulus. This aligns with prior findings that the contents of both perception and thought are linked to phase-based oscillatory cycles in alpha frequencies, where faster neural speeds facilitate more efficient neural synchronization and more deliberate and on-task thoughts (Cohen, 2014b; Hua et al., 2022; Mierau et al., 2017; Wolff, de la Salle, et al., 2019).

SE quantifies the unpredictability of neural oscillations, capturing the brain's dynamic readiness for external demands (Lau et al., 2022; Lechner & Northoff, 2023). Higher SE is thus crucial for facilitating flexibility to respond to external stimuli (Lau et al., 2022; Pedersen et al., 2017; Saxe et al., 2018). On-task and deliberate thoughts exhibit higher SE, suggesting enhanced flexibility in the preparatory state from a neuronal perspective (Lau et al., 2022; Pedersen et al., 2017; Saxe et al., 2018). Our mediation model underscores the relationship between FS and SE, where FS serves as a precursor driving neural flexibility. Deliberate and on-task thoughts increase FS, which subsequently raises SE, creating a dynamic pre-stimulus neural state that supports subsequent phase alignment during task execution. Notably, both thought dimensions, that is, deliberate control and task relatedness converged on the same mechanistic pathway: their influence on SE was fully mediated by FS. This trial-level mediation effect was statistically significant for both dimensions in the single-level models, highlighting the central role of phase dynamics, e.g., FS as a commonly shared neural mechanism through which different dimensions of thought shape pre-stimulus neural speed and flexibility. Importantly, these indirect effects were no longer significant in multilevel models that explicitly separated within- and between-subject variance, although the FS → SE pathway remained robust across levels. This discrepancy indicates that the apparent mediation likely reflects trial-to-trial variability; this is meaningful given that thoughts fluctuate on a trial-by-trial basis while this effect may be obscured when aggregating and averaging across subjects. Thus, while multilevel analyses provide a more conservative test, the significant trial-based mediation underscores the functional role of FS in linking both deliberate control and task relatedness to SE in a moment-to-moment way, that is, trial-based.

From Pre-Stimulus Neuronal Dynamics to Post-Stimulus Neural Activity and Behavior

The optimal phase alignment at stimulus onset is essential for effective post-stimulus synchronization (Van Diepen & Mazaheri, 2018). High SE enhances flexibility of neural oscillations, leading to higher phase alignment to the optimal phase, and thus higher ITPC and consequently, shorter RT. In contrast, lower ITPC, stemming from disrupted phase dynamics, slows RTs. The cascading effects of pre-stimulus phase-based amplitude variability (SE) to ITPC and RT, further highlight the pivotal role of phase dynamics in linking thought through neural readiness, and ultimately, to behavior.

Together, these findings support the plausibility of a mechanistic pathway from thought to behavior: **Ongoing Thought → Pre-stimulus FS → Pre-stimulus SE → Post-stimulus ITPC → Post-stimulus RT**. This pathway illustrates how ongoing thoughts influence pre-stimulus phase dynamics, which in turn associate with post-stimulus phase synchronization and behavioral performance. Moreover, as supported by our control analyses like phase shuffling, this study provides compelling evidence that phase dynamics, rather than the magnitude of the signal are critical in linking characteristics of thought to task performance. FS determines the changes in speed of phase cycles, while SE captures phase-based amplitude variability, both of which are crucial for achieving optimal phase alignment at stimulus onset. The critical role of phase was further validated by phase-shuffling analyses, which disrupted key relationships and confirmed that phase continuity is essential for neural synchronization and behavioral efficiency.

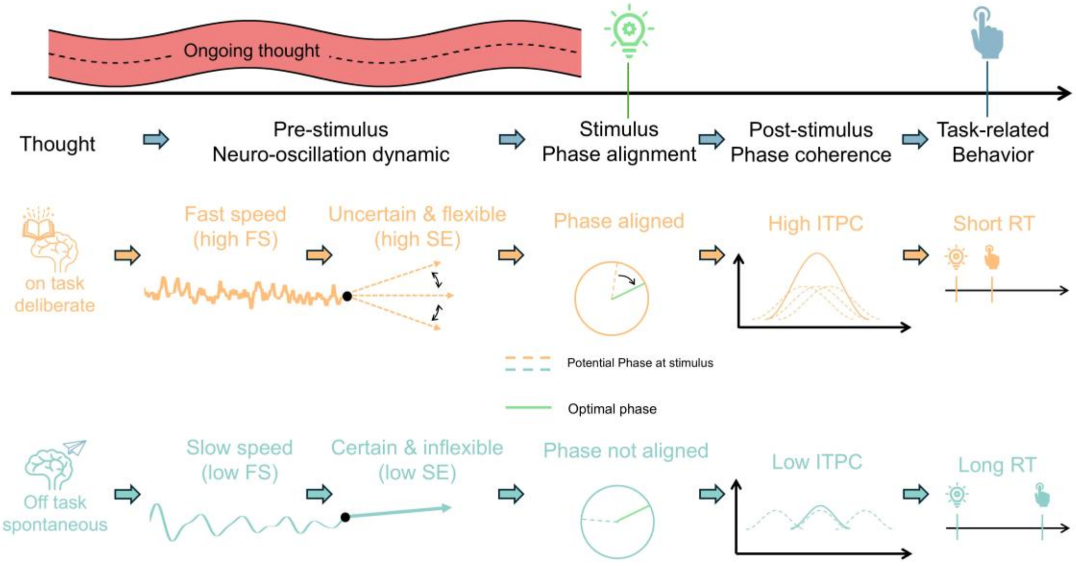


Figure 7: Mechanistic pathway linking thought dimensions to behavioral outcomes through neural dynamics. This figure illustrates the relationship between thought dimensions, pre-stimulus neural oscillations, post-stimulus phase coherence, and reaction time (RT). **Thought Dimensions:** On-task deliberate thoughts (orange) are associated with faster RTs, while off-task spontaneous thoughts (blue) correspond to slower RTs, highlighting their influence on task performance. **Pre-Stimulus Neuro-oscillation dynamics:** On-task deliberate thoughts enhance pre-stimulus FS (neural phase-based speed) and SE (phase uncertainty). Higher FS enables faster neural oscillations, while increased SE facilitates more flexible neural oscillations, preparing for

optimal phase alignment at stimulus onset. Conversely, off-task spontaneous thoughts result in lower pre-stimulus FS and SE, characterized by slower oscillations and reduced flexibility, diminishing the potential for phase alignment. **Phase alignment and Post-Stimulus Dynamics:** High FS and SE in the pre-stimulus phase increase the probability of higher phase alignment at stimulus onset, leading to higher post-stimulus ITPC in the post-stimulus phase. This phase synchronization enhances task performance by reducing RT. Low FS and SE result in lower phase alignment at stimulus onset, leading to lower ITPC, and slower RTs. **Behavioral Outcome:** The pathway—Ongoing Thought → pre-stimulus FS → pre-stimulus SE → post-stimulus ITPC → Post-stimulus RT—emphasizes how thought states (on-task deliberate vs. off-task spontaneous) affect pre-stimulus neural preparation and post-stimulus task execution, ultimately affecting behavioral responses.

Limitations

Due to time constraints of 10 minutes, in order to ensure a longer pre-stimulus period to generate and assess ongoing thought, each participant completed only 20 trials in the RTT task, similar to previous studies (Rostami et al., 2022; Vanhaudenhuyse et al., 2011). Although ITPC analysis can be conducted based on this number of trials (Cohen, 2014a), it is generally believed that a higher number of trials would better ensure the robustness of ITPC. While the number of trials was sufficient for the current investigation, in future studies, increasing the number of trials could help improve the reliability of ITPC.

In addition, we employed the relatively simple RTT paradigm. Future studies should adopt more sophisticated paradigms, such as the Stroop task, to enable a more fine-grained investigation of higher-level cognitive processes.

An additional limitation concerns the mediation results. In single-trial analyses, both deliberate control and task relatedness significantly influenced SE through FS, whereas in multilevel models, these indirect effects were not significant at either the within- or between-subject level. This divergence suggests that the mediation pathway is most pronounced when capturing trial-level variability, but may be attenuated once one averages across trials as when the hierarchical structure is modeled. However, the number of clusters/subjects was relatively small (N = 40) for which reason our between-subject power was limited; this could also contribute to the absence of significance of the mediation analyses, especially those conducted at the subject level which showed relatively modest post-hoc power estimates (approximately 0.45–0.56). Although these values are below the conventional threshold for strong power, they still fall within a range considered adequate for exploratory or theory-driven models. Future work with larger samples and more trials will be necessary to determine whether these trial-level mediation effects generalize robustly across analytic levels.

Conclusion

This study suggests a plausible pathway linking distinct dimensions of thought to behavior through pre- and post-stimulus neural phase dynamics, though further work is needed to confirm the full mechanistic sequence. On-task deliberate thoughts enhance phase-based FS and SE during the pre-stimulus period. This, in turn, enhances the flexibility of neural oscillation, and thus increases the likelihood of higher coherence of the ongoing phase dynamics with the external stimulus, as manifest in higher post-stimulus ITPC. This cascade results in faster RT, emphasizing the key role of the brain's neuronal dynamics in connecting ongoing thoughts to behavior through pre-post-stimulus phase dynamics. Our findings demonstrate novel insights into how our ongoing thoughts affect task-related behavior and cognition.

General Discussion

The aim of this thesis was to investigate the multidimensional nature of spontaneous thought and its underlying neurodynamic mechanisms. Specifically, we examined how different dimensions of thought: task-relatedness, thought content quantity, orientation, and deliberate control, are tracked by distinct yet interrelated neural oscillatory dynamics, including phase dynamics, neural timescales, spontaneity, and entropy. Across three empirical studies employing EEG and behavioral measures, we found that these thought dimensions are neither entirely overlapping nor fully independent but rather interact in nuanced ways to be associated with both cognitive performance and neural oscillations.

The Multidimensionality of Spontaneous Thought

One of the central premises of this dissertation is that spontaneous thought cannot be adequately captured by a single dimension (Christoff et al., 2016, 2018; Smallwood & Schooler, 2006). Instead, spontaneous thought consists of multiple interacting dimensions, each supported by distinct neural processes. Our results confirm this view, demonstrating that while different dimensions of thought interact, they also operate on distinguishable behavioral and neural timescales. Across all three studies, thought states were assessed using thought-probe measures. Following previous literature, we employed categorical thought probes in Study 1 (Smallwood et al., 2008; Smallwood & Schooler, 2006). Importantly, results from Study 2 revealed that the behavioral impact of thought exhibits increased variability at intermediate states—such as at the boundary between on-task and off-task thought—thereby providing empirical justification for the use of categorical thought probes to capture robust distinctions between thought states. In contrast, continuous thought probes were employed in Studies 2 and 3. This choice was motivated by the advantage of continuous visual analog scales (VAS) in enabling nonlinear analyses or mediation analyses. Specifically, continuous measures allow us to characterize graded changes in thought and to model potentially nonlinear or mediative relationships between thought states, neural dynamics, and behavior.

In **Study 1**, we showed that task-relatedness and thought content quantity are interdependent, with on-task thoughts predominantly involving a single content, whereas off-task thoughts were characterized by multiple, simultaneous contents. The tracking of these thought dynamics was supported by phase-related changes in alpha and theta FS (**Figure D**).

In **Study 2**, we demonstrated that task-relatedness and thought orientation are dissociable along both behavioral and neural timescales. Task-related thoughts were associated with shorter timescales, as reflected in PE and topographic similarity during fast finger tapping. In contrast, thought orientation was linked to longer timescales, as observed in PE and topographic similarity during slow finger tapping (**Figure D**).

In **Study 3**, we further established that task-relatedness and deliberate control are interdependent and they interact with neural oscillatory phase measures. Specifically, on-task and deliberate thoughts were associated with higher pre-stimulus oscillation speed (FS) and greater phase flexibility (SE). These neural dynamics facilitated stronger post-stimulus phase alignment, as indexed by ITPC, and ultimately led to faster reaction times (RT). Together, these findings strongly support a multidimensional framework for spontaneous thought, wherein distinct thought dimensions contribute to the complexity of ongoing thought (**Figure D**).

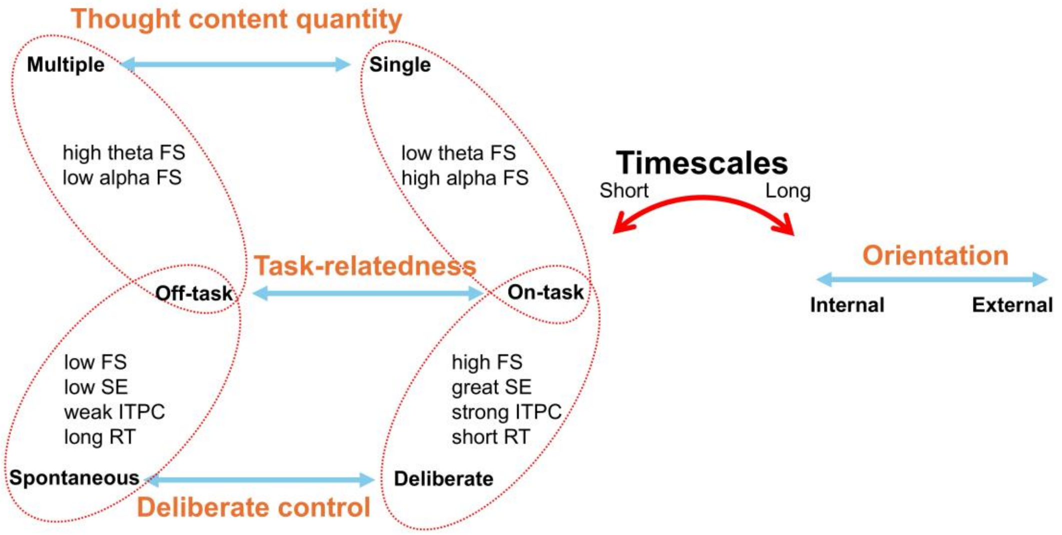


Figure D. Neural and Behavioral Signatures of Thought Dimensions Across Studies. In **Study 1** we found that task-relatedness and thought content quantity are interdependent, with on-task thoughts predominantly involving a single content and off-task thoughts characterized by multiple contents. These dynamics are tracked by phase-based changes in alpha and theta peak frequency (FS), with on-single thoughts showing increased alpha FS and decreased theta FS, while off-multiple thoughts exhibit the reverse pattern. In **Study 2** we found that task-relatedness and thought orientation are dissociable based on behavioral and neural timescales. Task-related thoughts operate at shorter timescales. In **Study 3** we found that task-relatedness and deliberate control are interdependent and interact with neural oscillatory phase measures. On-task and deliberate thoughts are associated with higher pre-stimulus oscillation speed (FS) and greater phase flexibility (SE), facilitating stronger post-stimulus phase alignment (ITPC) and leading to faster reaction times (RT). Across all three studies, distinct dimensions of thought—task-relatedness, thought content quantity, thought orientation, and deliberate control—interact yet operate on separable behavioral and neural timescales, supporting the multidimensional nature of spontaneous thought.

Task-relatedness during resting-state thought

In Study 3, we also examined thought ratings during the resting-state condition. During this condition, participants were not required to perform any explicit task; instead, they were instructed only to maintain fixation on a central cross and remain relaxed. Importantly, they were not instructed to direct, constrain, or regulate their thoughts in any specific way. As a result, the resting-state condition did not provide an explicit external task that could clearly anchor the distinction between being "on-task" versus "off-task." This design was intentional, as it minimizes demand characteristics and evaluation-related pressures that can arise when participants are expected to perform or succeed at a task, thereby allowing a more natural sampling of ongoing thought.

If participants had been uncertain about how to interpret task-relatedness under these conditions, such ambiguity would be expected to reduce the consistency or coherence of their self-reports. However, several results suggest that this was not the case. First, task-relatedness ratings in the resting state did not differ significantly from those obtained in the task condition, indicating that participants applied the rating scale in a comparable manner across contexts. Second, the association between task-relatedness and deliberate control remained significant in both resting and task conditions, suggesting a stable internal structure in how these dimensions were evaluated.

One possibility is that, in the absence of an explicit task, participants may have implicitly treated fixation on the cross as a task, potentially conflating task-relatedness with deliberate control. The observed data, however, argue against such an interpretation. Specifically, task-relatedness and deliberate control showed greater dissociation in the resting state than in the task condition, indicating that participants were able to distinguish between these dimensions even when no formal task was present. Together, these findings suggest that task-relatedness reflects a broader, internally defined reference frame—such as engagement with a self-generated goal, focus, or mental anchor—rather than merely compliance with externally imposed task demands. While individual interpretations of task-relatedness during rest may vary, the overall pattern of results supports the reliability and construct validity of this dimension across both task and resting contexts. Nonetheless, it is worth pointing out that this issue is far from resolved, is a topic of great debate, interest, and ongoing investigation in the extant literature (He, 2013; Huang et al., 2017).

Alpha and Theta Oscillations Track Task-Relatedness and Thought Content Quantity

Task-relatedness and thought content quantity are coupled with each other on both behavioral and neural levels

This study investigated how task-relatedness (on-task vs. off-task) and thought content quantity (single vs. multiple) interact, and whether they can be tracked by distinct neural oscillatory markers. While previous studies have largely focused on task-relatedness alone (Mills et al., 2018; Christoff et al., 2016), our findings demonstrate that thought content quantity is a critical factor in understanding the complexity of off-task thought. Behaviorally, we observed that on-task thoughts were predominantly single-content, whereas off-task thoughts involved multiple simultaneous contents. Neuronally, the distances of both FS and FP timeseries between off-task and multiple-contents vs. on-task and single-content thought are the smallest on both alpha and theta bands, indicating the coupling between the two thought dimensions.

Task-relatedness and thought content quantity can be tracked by alpha and theta FS

Post-stimulus EEG analyses revealed that on-single thoughts were characterized by an increase in alpha FS and a decrease in theta FS, whereas off-multiple thoughts exhibited the opposite pattern. Importantly, these changes were observed in phase-based peak frequency measures (FS) but not in power-based analyses (FP), suggesting that phase-related oscillatory dynamics may be more sensitive than traditional power measures in tracking thought states.

The phase-based measures like FS reflect neural and cognitive processes, with higher neuronal input leading to increased population activity and peak frequency, particularly in the alpha band (Cohen, 2014b; Gulbinaite et al., 2017; Mierau et al., 2017). Therefore, alpha FS increases during on-single thoughts, likely reflecting externally driven input. In contrast, off-multiple thoughts—being task-unrelated—are associated with increased theta peak frequency, suggesting internally generated neuronal input. (Axmacher et al., 2010; Moran et al., 2010; Wolinski et al., 2018).

This study shows that off-multiple thoughts, characterized by internally generated multiple contents, are associated with increased theta peak frequency and decreased alpha peak frequency, indicating a shift from external stimuli to internal thought contents (Axmacher et al., 2010; Moran et al., 2010; Wolinski et al., 2018). In contrast, on-single thoughts exhibits the opposite pattern, reflecting perceptual coupling (Cohen, 2014b; Gulbinaite et al., 2017; Mierau et al., 2017).

Task-Relatedness and Thought Orientation Operate on Distinct Neural and Behavioral Timescales

Task-relatedness and thought orientation can be distinguished by behavioral timescales

The first study suggests that an off-task thought could be a perceptual decoupled (internal) thought, while and on-task thought could be a perceptual coupled (external) thought. However, recent studies suggest that thought orientation and task-relatedness could be distinct dimensions, differing in their neural correlates and temporal dynamics (Kucyi et al., 2018; Rostami et al., 2022; Vanhaudenhuyse et al., 2011). Therefore, our second study examined whether task-relatedness and thought orientation could be distinguished based on their behavioral and neural timescales. While some models have treated these dimensions as overlapping (Smallwood & Schooler, 2006), our results reveal that they operate on distinct timescales. Using self-paced finger tapping, we found that task-relatedness was associated with shorter behavioral timescales, reflected in fast finger tapping, whereas thought orientation was linked to longer timescales, reflected in slow finger tapping.

Crucially, nonlinear modeling revealed distinct mechanistic profiles for each dimension. GAMs and Bayesian mediation analysis showed that task-relatedness was associated with a nonlinear suppression effect, particularly during slow tapping, where intermediate VAS ratings (near 50) corresponded to higher behavioral variance. In contrast, thought orientation maintained robust, linear associations with PE across timescales, suggesting stable integration mechanisms. This dissociation highlights a mechanistic difference in how the two dimensions influence behavior: task-relatedness, operating on a shorter timescale, fails to integrate over extended durations (as in slow tapping), leading to greater variability and nonlinear fluctuations in behavior. This is likely because task-relatedness primarily supports temporal segregation—the rapid parsing of input over short intervals—which renders it poorly suited for processing information distributed across longer timescales. In contrast, thought orientation is characterized by stable linear associations with PE across both short and long timescales, suggesting that it engages more robust temporal integration mechanisms.

Task-relatedness and thought orientation can be distinguished by neural timescales

Topographic similarity reflects the moment-to-moment stability of neural activity (Luo et al., 2024; Tian & Huber, 2008), which directly quantifies how past neural states influence present ones (Luo et al., 2024), making it a useful measure of temporal integration mechanisms. Higher topographic similarity over shorter timescales indicates rapid updating of recent information that shapes immediate processing. This pattern aligns with task-relatedness and reflects temporal segregation, which emphasizes the prioritization of immediate external input (Lechner & Northoff, 2023; Pöppel, 2009; Thönes & Stocker, 2019). In contrast, higher topographic similarity over longer timescales suggests that past neural states exert a sustained influence on current processing. This pattern supports thought orientation and reflects temporal integration (Lechner & Northoff, 2023; Pöppel, 2009; Thönes & Stocker, 2019). Such integration depends on longer-duration cognitive processes, including memory and introspection (Lechner & Northoff, 2023; Pöppel, 2009; Thönes & Stocker, 2019). By showing that different thought dimensions are governed by distinct timescales, this study contributes to the growing body of evidence supporting the hierarchical organization of thoughts based on temporal dynamics (Golesorkhi, Gomez-Pilar, Tumati, et al., 2021; Kiebel et al., 2008; Northoff et al., 2020a, 2020b).

Moreover, GAM and Bayesian mediation analyses uncovered nonlinear effect of topographic similarity by thought ratings, further supporting the dissociation. Specifically, task-relatedness showed nonlinear effects during fast tapping, and thought orientation exhibited nonlinear effect during slow tapping. Contrary to traditional assumptions of linear neural dynamics (Barron et al., 2011; Smallwood & Schooler, 2006). This perspective helps explain why thought ratings is associated with topographic similarity in a nonlinear fashion: topographic similarity directly quantifies how the neural state at a prior timepoint shapes the current one. As such, it serves as a measure of cross-temporal integration in neural processing. These findings provide converging neural-level evidence for the existence of distinct temporal profiles across thought dimensions: task-relatedness is associated with a shorter timescale and predominantly facilitates *temporal segregation*, while thought orientation aligns with a longer timescale and supports *temporal integration*.

This study extends the Perceptual Decoupling Hypothesis by introducing a two-dimensional framework for thought (**Figure E**). Traditionally, perceptual decoupling hypothesis suggests a horizontal continuum where perceptual coupling (on-task, external thoughts) and perceptual decoupling (off-task, internal thoughts) are inherently linked—i.e., being on-task is always tied to external focus, while off-task states align with internal thoughts (Schooler et al., 2011; Smallwood & Schooler, 2006). Our first study indirectly supported this by showing that off-task thoughts tend to be internally oriented, while on-task thoughts are more externally focused. However, in our second study, we introduce a vertical dissociation based on temporal scale. Task-relatedness is associated with short timescales, whereas thought orientation operates on longer timescales. This finding suggests that the two dimensions can be dissociated through their distinct neural and behavioral temporal profiles. This suggests that perceptual decoupling/coupling operates across two distinct temporal layers—one tracking short-term external inputs for on-task engagement and another supporting long-term integration for internally-oriented thoughts. Our findings reveal that perceptual decoupling hypothesis is not merely a single-axis model but functions within a dynamic interplay of timescales, associated with the flexibility of thought processes across both external and internal domains.

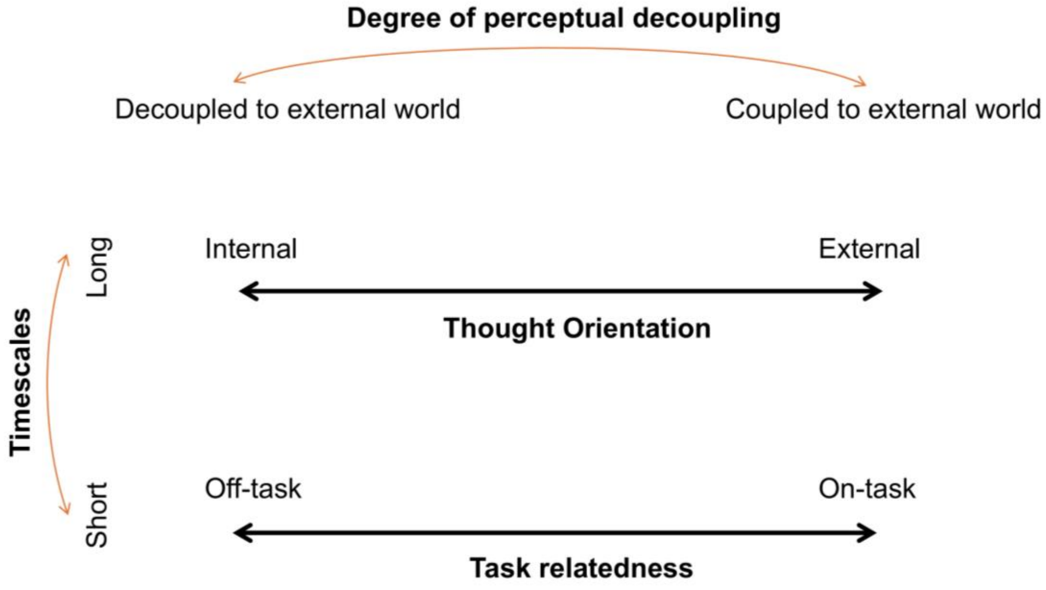


Figure E. A Two-Dimensional Framework of Thought. Schematic representation of the proposed two-dimensional model extending the perceptual decoupling hypothesis. **The horizontal axis** represents the traditional perceptual coupling-decoupling continuum, where on-task thoughts are predominantly associated with external focus and off-task thoughts with internal orientation, as suggested by previous models. **The vertical axis** introduces a novel dissociation based on timescales, distinguishing task-relatedness (short timescales) from thought orientation (long timescales) at both behavioral and neural levels. This framework reveals that perceptual decoupling is not strictly tied to a single axis but rather operates across two distinct temporal layers—one for fast, externally driven on-task and another for slower, internally oriented thought. This dynamic interplay of timescales suggests greater flexibility in how perceptual decoupling shapes thought processes across external and internal domains.

Thoughts impact neural states based on phase dynamics

Our second study further demonstrated that the influence of thought on neural states is phase-based. Specifically, we found that topographic similarity was tightly coupled with PLV, a measure of phase coherence. Moreover, disrupting the phase structure abolished the relationship between topographic similarity and thought dimensions, confirming that the observed double dissociation is more closely associated with distributed phase coherence than with amplitude-based measures. These findings suggest that the influence of thought may be underpinned by phase-based neural coordination across timescales, rather than by localized power fluctuations.

Building on this, our third study focused explicitly on this question, examining two closely related dimensions: task-relatedness and deliberate constraint. Using a simple reaction time paradigm, we investigated how these dimensions of thought influence behavior across time—specifically, how pre-stimulus thought states shape post-stimulus behavioral responses, and whether this influence is mediated by neural phase dynamics.

Task-Relatedness and Deliberate Control: Pre-stimulus thought shapes post-stimulus task-related performance through phase dynamics

Our third study investigated how pre-stimulus thought influences post-stimulus task performance through neural dynamics. The results revealed that phase-based oscillatory dynamics serve as the mechanistic link between pre-stimulus thoughts and post-stimulus behavior.

Thought Dimensions and Pre-Stimulus Neural Dynamics

We examined how on-task vs. off-task and deliberate vs. spontaneous thoughts influence pre-stimulus neuro-oscillatory dynamics, specifically neural speed (FS) and neural flexibility (SE). we found that: 1) On-task and deliberate thoughts were associated with higher FS (faster oscillations) and increased SE (greater neural flexibility). 2) Off-task and spontaneous thoughts showed lower FS and reduced SE, indicating decreased preparatory neural dynamics. 3) A mediation model confirmed that FS drives SE, positioning oscillation speed as a key determinant of neural flexibility.

Pre-Stimulus Neural Activity and Post-Stimulus Phase Coherence

In the next step, we investigated whether pre-stimulus FS and SE impact post-stimulus ITPC, a measure of neural phase alignment. We found that higher FS and SE before stimulus onset led to increased ITPC, indicating stronger neural synchronization across trials. This result suggests that enhanced pre-stimulus neural dynamics facilitate phase coherence at stimulus onset, supporting efficient cognitive processing.

Post-Stimulus Phase Coherence and Behavioral Performance

Finally, we examined how ITPC impacts RT, providing a neural mechanism for thought-behavior interactions. We found that higher ITPC was associated with faster RTs, demonstrating that better neural phase alignment improves task performance.

In conclusion, a pathway linking pre-stimulus thought and post-stimulus behavior emerged: On-task and deliberate thoughts are associated with increased FS and SE, which in turn correlate with stronger ITPC and faster RTs, suggesting a potential neural pathway linking thought states to task performance. Our phase shuffling results further confirmed that phase dynamics mediate the link between thought and behavior. This highlights the pivotal role of phase dynamics in shaping both thought and behavior. These findings provide a novel framework for understanding how ongoing thought influences task execution through oscillatory mechanisms.

These results further extend the conclusions of Study 2, suggesting that the association between thought and cross-temporal neural dynamics is primarily phase-based, rather than being explained by amplitude alone.

Limitations and Future Directions

In this thesis, we investigated the multidimensional nature of spontaneous thought by analyzing the neurodynamic correlations of several key thought dimensions: task-relatedness, thought content quantity, deliberate control, and thought orientation. While our findings contribute to the development of a theoretical framework for understanding spontaneous thought, several limitations should be noted.

First, all three studies employed correlational designs, and thus, any causal interpretations should be avoided. Although we observed significant associations between neural dynamics (e.g., phase-based oscillatory features) and dimensions of thought, these findings do not imply direct causality. Future work using experimental or longitudinal designs is needed to better understand potential causal mechanisms.

Second, the results from each study require independent replication. Given the complexity of EEG data and inter-individual variability, validating these findings in larger and more diverse samples is essential.

Third, the generalizability of the results is limited by the relatively homogenous sample used in the current work. Participants were primarily young, healthy, university-educated adults. Future research should explore whether similar neurodynamic patterns can be observed across individuals with varying demographic, cultural, educational, and clinical backgrounds.

Fourth, the present work relies on self-report measures to assess thought dimensions, which are inherently susceptible to biases such as social desirability and potential reluctance to report off-task states. To mitigate this concern, participants showing invariant response patterns were excluded, and a control analysis in Study 3 examined thought ratings during the resting state, where no explicit task or performance demands were present. Task-relatedness ratings were comparable across resting and task contexts, and their association with deliberate control was preserved, suggesting consistent application of the rating scales. Moreover, greater dissociation between task-relatedness and deliberate control in the resting state argues against a simple conflation of these dimensions. Nevertheless, future work integrating self-report with objective or physiological indices of ongoing thought would further strengthen measurement validity.

Fifth, each study examined different thought dimensions in isolation. Although this approach allowed for clear operationalization and analysis, it may have overlooked potential interactions among dimensions. Future studies could address this by examining multiple dimensions concurrently, for example through clustering or multivariate analysis, thereby capturing more complex cognitive profiles.

Finally, the present work emphasizes the temporal properties of neural oscillations associated with thought, particularly phase-based dynamics. Future studies integrating modalities with higher spatial precision, such as MEG and fMRI, will be crucial for elucidating how these temporal dynamics are embedded within large-scale spatial networks supporting thought.

From Thought Dynamics to Clinical Intervention

In this dissertation, to briefly recap: we examined the relationships among multiple dimensions of thought, including task-relatedness, thought orientation, thought content quantity, and deliberate control, and investigated the hypothesized association with neural oscillatory phase basis of thought. In particular, we found that thought states are systematically associated with peak frequency sliding in the alpha and theta bands, reflecting differences in the speed of neural oscillatory phase dynamics. Specifically, thoughts characterized by reduced task engagement are typically accompanied by slower alpha oscillations (Studies 1 and 3) and faster theta oscillations (Study 1).

With respect to any possible links of these findings to clinical populations, converging evidence from an independent study on major depressive disorder (MDD) has shown that, compared with healthy individuals, patients with depression also exhibit slower alpha oscillations and faster theta oscillations (Wolff, de la Salle, et al., 2019) . These oscillatory patterns are likely related to characteristic features of depressive rumination, which is commonly manifested as off-task and internally oriented thought.

Taken Together, these findings suggest that depression may not represent a qualitatively distinct cognitive state, but rather an extreme position along a continuum of neural-thought dynamics observed in healthy cognition. Accordingly, future research may explore neuromodulation approaches, such as transcranial magnetic stimulation (TMS) or transcranial alternating current stimulation (tACS), to change neural oscillatory properties (e.g., peak frequency) toward ranges observed in healthy individuals, thereby potentially alleviating depressive symptoms.

Theoretical Implications

The broader significance of this work lies in reframing spontaneous thought as a dynamic, multidimensional process grounded in neural dynamics. By demonstrating that different thought dimensions are associated with distinct phase-based properties, timescales, and levels of neural entropy, this thesis moves the field beyond static descriptions of mind-wandering toward a mechanistic understanding of how thought unfolds over time and shapes behavior. This framework provides a foundation for integrating previously fragmented findings and opens new avenues for translational research targeting maladaptive thought dynamics.

Extending the family resemblance view of spontaneous thought

The concept of *family resemblance* originates from Wittgenstein's philosophical framework, which suggests that certain categories do not have a single defining feature but instead consist of a network of overlapping similarities (Wittgenstein, 2009). Applied to spontaneous thought, this view implies that spontaneous thoughts like mind wandering should not be defined by a singular, rigid characteristic but rather by a set of interrelated thought dimensions that share commonalities without a fixed boundary (Seli, Kane, Smallwood, et al., 2018).

The findings of this thesis advance upon the family resemblance framework of spontaneous thought. By integrating neurodynamic and cognitive dimensions of thought, we provide empirical evidence supporting the idea that spontaneous thoughts encompass a heterogeneous set of thought dimensions, rather than being defined by a single characteristic. This perspective is consistent with the family resemblance approach. Under this framework, spontaneous thought is conceptualized as a cluster of related yet distinct thought types. These types share overlapping features but lack a single defining criterion (Seli, Kane, Metzinger, et al., 2018; Seli, Kane, Smallwood, et al., 2018).

Extending the Spatio-Temporal Theory of Spontaneous Thought (STTT)

In addition to supporting the family resemblance view—which emphasizes associations among different thought dimensions—our findings provide empirical support for the *Spatio-Temporal Theory of Spontaneous Thought (STTT)*. Specifically, they demonstrate how distinct types of thought can be differentiated based on their underlying neural dynamic features (Northoff, 2024; Northoff et al., 2020a, 2020b). This theory posits that different dimensions of thought are governed by distinct temporal and spatial neural dynamics (Northoff, 2024; Northoff et al., 2020a, 2020b). Our results extend STTT by demonstrating that task-relatedness is associated with short temporal scales, while thought orientation operates at longer temporal scales. This provides further neurophysiological support for STTT's. According to STTT, spontaneous thought emerges from the hierarchical organization of neural timescales. Shorter timescales are responsible for immediate task-related processing. In contrast, longer timescales support internally generated, unconstrained thought processes (Murray et al., 2014; Raut et al., 2020).

Moreover, we propose that phase dynamics serve as the mechanistic bridge linking neural dynamic, thought dimensions and behavioral outcomes. The observed relationships between phase-based measures like PLV, FS, SE and ITPC and behavior indicate that neural coordination mechanisms play a critical role in structuring the spatio-temporal landscape of thought. This suggests that phase dynamics may play a key role in how spontaneous thought arises, integrates and transfers information over time, and ultimately shapes responses to external stimuli. (Cohen, 2014b; Lau et al., 2022; Wolman et al., 2023).

References

Aboy, M., Cuesta-Frau, D., Austin, D., & Mico-Tormos, P. (2007). Characterization of Sample Entropy in the Context of Biomedical Signal Analysis. *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 5942–5945. https://doi.org/10.1109/IEMBS.2007.4353701

Alperin, B. R., Christoff, K., Mills, C., & Karalunas, S. L. (2021). More than off-task: Increased freely-moving thought in ADHD. *Consciousness and Cognition*, *93*, 103156. https://doi.org/10.1016/j.concog.2021.103156

Alpert, G. F., Hein, G., Tsai, N., Naumer, M. J., & Knight, R. T. (2008). Temporal Characteristics of Audiovisual Information Processing. *The Journal of Neuroscience*, *28*(20), 5344–5349. https://doi.org/10.1523/JNEUROSCI.5039-07.2008

Amrani, A. K., & Golumbic, E. Z. (2020). Spontaneous and stimulus-driven rhythmic behaviors in ADHD adults and controls. *Neuropsychologia*, *146*, 107544.

Amrani, A. K., & Golumbic, E. Z. (2021). Memory-paced tapping to auditory rhythms: Effects of rate, speech and motor-engagement. *bioRxiv*, 2021.07.13.452153.

Andrews-Hanna, J. R., Irving, Z. C., Fox, K. C. R., Spreng, R. N., & Christoff, K. (2018). The Neuroscience of Spontaneous Thought: An Evolving Interdisciplinary Field. In *The Oxford handbook of spontaneous thought: Mind-wandering, creativity, and dreaming* (pp. 1–47).

Andrews-Hanna, J. R., Reidler, J. S., Huang, C., & Buckner, R. L. (2010). Evidence for the default network's role in spontaneous cognition. *Journal of Neurophysiology*, *104*(1), 322–335. https://doi.org/10.1152/jn.00830.2009

Andrews-Hanna, J. R., Smallwood, J., & Spreng, R. N. (2014). The default network and self-generated thought: Component processes, dynamic control, and clinical relevance. *Annals of the New York Academy of Sciences*, *1316*(1), 29–52. https://doi.org/10.1111/nyas.12360

Andrillon, T., Burns, A., Mackay, T., Windt, J., & Tsuchiya, N. (2021). Predicting lapses of attention with sleep-like slow waves. *Nature Communications*, *12*(1), 1–12. https://doi.org/10.1038/s41467-021-23890-7

Ao, Y., Klar, P., Catal, Y., Wang, Y., & Northoff, G. (2025). Infra-slow scale-free dynamics modulate the connection of neural and behavioral variability during attention. *Communications Biology*, *8*(1), 1057. https://doi.org/10.1038/s42003-025-08448-3

Arnau, S., Löffler, C., Rummel, J., Hagemann, D., Wascher, E., & Schubert, A. L. (2020). Inter-trial alpha power indicates mind wandering. *Psychophysiology*, *57*(6), 1–14. https://doi.org/10.1111/psyp.13581

Atchley, R., Klee, D., & Oken, B. (2017). EEG Frequency Changes Prior to Making Errors in an Easy Stroop Task. *Frontiers in Human Neuroscience*, *11*(October), 1–7. https://doi.org/10.3389/fnhum.2017.00521

Axmacher, N., Henseler, M. M., Jensen, O., Weinreich, I., Elger, C. E., & Fell, J. (2010). Cross-frequency coupling supports multi-item working memory in the human hippocampus. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(7), 3228–3233. https://doi.org/10.1073/pnas.0911531107

Babo-Rebelo, M., Richter, C. G., & Tallon-Baudry, C. (2016). Neural responses to heartbeats in the default network encode the self in spontaneous thoughts. *Journal of Neuroscience*, *36*(30), 7829–7840. https://doi.org/10.1523/JNEUROSCI.0262-16.2016

Baird, B., Smallwood, J., Lutz, A., & Schooler, J. W. (2014). The Decoupled Mind: Mind-wandering Disrupts Cortical Phase-locking to Perceptual Events. *Journal of Cognitive Neuroscience*, *26*(11), 2596–2607. https://doi.org/10.1162/jocn_a_00656.

Baldwin, C. L., Roberts, D. M., Barragan, D., Lee, J. D., Lerner, N., & Higgins, J. S. (2017). Detecting and quantifying mind wandering during simulated driving. *Frontiers in Human Neuroscience*, *11*(August), 1–15. https://doi.org/10.3389/fnhum.2017.00406

Barron, E., Riby, L. M., Greer, J., & Smallwood, J. (2011). Absorbed in Thought: The Effect of Mind Wandering on the Processing of Relevant and Irrelevant Events. *Psychological Science*, *22*(5), 596–601. https://doi.org/10.1177/0956797611404083

Barttfelda, P., Uhriga, L., Sitta, J. D., Sigmane, M., Jarrayaa, B., & Dehaene, S. (2015). Signature of consciousness in the dynamics of resting-state brain activity. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(3), 887–892. https://doi.org/10.1073/pnas.1418031112

Baseer, A., Weddell, S. J., & Jones, R. D. (2017). Prediction of microsleeps using pairwise joint entropy and mutual information between EEG channels. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 4495–4498. https://doi.org/10.1109/EMBC.2017.8037855

Bastian, M., & Sackur, J. (2013). Mind wandering at the fingertips: Automatic parsing of subjective states based on response time variability. *Frontiers in Psychology*, *4*. https://doi.org/10.3389/fpsyg.2013.00573

Bocharov, A. V., Knyazev, G. G., Savostyanov, A. N., Astakhova, T. N., & Tamozhnikov, S. S. (2019). EEG dynamics of spontaneous stimulus-independent thoughts. *Cognitive Neuroscience*, *10*(2), 77–87. https://doi.org/10.1080/17588928.2018.1534820

Bodalski, E. A., Knouse, L. E., & Kovalev, D. (2018). Adult ADHD, Emotion Dysregulation, and Functional Outcomes: Examining the Role of Emotion Regulation Strategies. *Journal of Psychopathology and Behavioral Assessment*. https://doi.org/10.1007/s10862-018-9695-1

Bodart, O., Gosseries, O., Wannez, S., Thibaut, A., Annen, J., Boly, M., Rosanova, M., Casali, A. G., Casarotto, S., Tononi, G., Massimini, M., & Laureys, S. (2017). Measures of metabolism and complexity in the brain of patients with disorders of consciousness. *NeuroImage: Clinical*, *14*, 354–362. https://doi.org/10.1016/j.nicl.2017.02.002

Boly, M., Balteau, E., Schnakers, C., Degueldre, C., Moonen, G., Luxen, A., Phillips, C., Peigneux, P., Maquet, P., & Laureys, S. (2007). Baseline brain activity fluctuations predict somatosensory perception in humans. *Proceedings of the National Academy of Sciences*, *104*(29), 12187–12192. https://doi.org/10.1073/pnas.0611404104

Braboszcz, C., & Delorme, A. (2011). Lost in thoughts: Neural markers of low alertness during mind wandering. *NeuroImage*, *54*(4), 3040–3047. https://doi.org/10.1016/j.neuroimage.2010.10.008

Brandmeyer, T., & Delorme, A. (2018). Reduced mind wandering in experienced meditators and associated EEG correlates. *Experimental Brain Research*, *236*(9), 2519–2528. https://doi.org/10.1007/s00221-016-4811-5

Brandmeyer, T., & Delorme, A. (2020). Meditation and the Wandering Mind: A Theoretical Framework of Underlying Neurocognitive Mechanisms. *Perspectives on Psychological Science*, *16*(1), 39–66. https://doi.org/10.1177/1745691620917340

Bravi, A., Longtin, A., & Seely, A. J. E. (2011). Review and classification of variability analysis techniques with clinical applications. *BioMedical Engineering Online*, *10*, 1–27. https://doi.org/10.1186/1475-925X-10-90

Bressler, S. L., & Menon, V. (2010). Large-scale brain networks in cognition: Emerging methods and principles. *Trends in Cognitive Sciences*, *14*(6), 277–290. https://doi.org/10.1016/j.tics.2010.04.004

Broadway, J. M., Franklin, M. S., & Schooler, J. W. (2015). Early event-related brain potentials and hemispheric asymmetries reveal mind-wandering while reading and predict comprehension. *Biological Psychology*, *107*, 31–43. https://doi.org/10.1016/j.biopsycho.2015.02.009

Buckner, R. L., & DiNicola, L. M. (2019). The brain's default network: Updated anatomy, physiology and evolving insights. *Nature Reviews Neuroscience*, *20*(10), 593–608. https://doi.org/10.1038/s41583-019-0212-7

Buzsaki, G. (2006). *Rhythms of the Brain*. Oxford university press.

Callard, F., Smallwood, J., Golchert, J., & Margulies, D. S. (2013). The era of the wandering mind? Twenty-first century research on self-generated mental activity. *Frontiers in Psychology*, *4*(891), 1–11. https://doi.org/10.3389/fpsyg.2013.00891

Canolty, R. T., & Knight, R. T. (2010). The functional role of cross-frequency coupling. *Trends in Cognitive Sciences*, *14*(11), 506–515. https://doi.org/10.1016/j.tics.2010.09.001

Casali, A. G., Gosseries, O., Rosanova, M., Boly, M., Sarasso, S., Casali, K. R., Casarotto, S., Bruno, M. A., Laureys, S., Tononi, G., & Massimini, M. (2013). A theoretically based index of consciousness independent of sensory processing and behavior. *Science Translational Medicine*, *5*(198). https://doi.org/10.1126/scitranslmed.3006294

Catalano, L. T., Reavis, E. A., Wynn, J. K., & Green, M. F. (2024). Peak alpha frequency in schizophrenia, bipolar disorder, and healthy volunteers: Associations with visual information processing and cognition. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, S2451902224001629. https://doi.org/10.1016/j.bpsc.2024.06.004

Chen, L., Yoon, S. Y., Leong, C. W., Martin, M., Ma, M., Pellegrino, R., Crandall, P. G., Seo, H.-S., Matthews, G., Szalma, J., Panganiban, A. R., Neubauer, C., & Warm, J. S. (2014). Profiling Task Stress With the Dundee Stress State Questionnaire. In *Food Research International* (Vol. 76, Issue 513). https://doi.org/10.1016/j.foodres.2014.12.027

Chennu, S., Finoia, P., Kamau, E., Allanson, J., Williams, G. B., Monti, M. M., Noreika, V., Arnatkeviciute, A., Canales-Johnson, A., Olivares, F., Cabezas-Soto, D., Menon, D. K., Pickard, J. D., Owen, A. M., & Bekinschtein, T. A. (2014). Spectral Signatures of Reorganised Brain Networks in Disorders of Consciousness. *PLoS Computational Biology*, *10*(10). https://doi.org/10.1371/journal.pcbi.1003887

Cheyne, J. A., Carriere, J. S. A., & Smilek, D. (2006). Absent-mindedness: Lapses of conscious awareness and everyday cognitive failures. *Consciousness and Cognition*, *15*(3), 578–592. https://doi.org/10.1016/j.concog.2005.11.009

Christoff, K. (2012). Undirected thought: Neural determinants and correlates. *Brain Research*, *1428*, 51–59. https://doi.org/10.1016/j.brainres.2011.09.060

Christoff, K., Gordon, A. M., Smallwood, J., Smith, R., & Schooler, J. W. (2009). Experience sampling during fMRI reveals default network and executive system contributions to mind wandering. *Proceedings of the National Academy of Sciences*, *106*(21), 8719–8724. https://doi.org/10.1073/pnas.0900234106

Christoff, K., Irving, Z. C., Fox, K. C. R., Spreng, R. N., & Andrews-Hanna, J. R. (2016). Mind-wandering as spontaneous thought: A dynamic framework. *Nature Reviews Neuroscience*, *17*(11), 718–731. https://doi.org/10.1038/nrn.2016.113

Christoff, K., Mills, C., Andrews-Hanna, J. R., Irving, Z. C., Thompson, E., Fox, K. C. R., & Kam, J. W. Y. (2018). Mind-Wandering as a Scientific Concept: Cutting through the Definitional Haze. *Trends in Cognitive Sciences*, *22*(11), 957–959. https://doi.org/10.1016/j.tics.2018.07.004

Cohen, M. X. (2014a). *Analyzing Neural Time Series Data Theory and Practice*.

Cohen, M. X. (2014b). Fluctuations in oscillation frequency control spike timing and coordinate neural networks. *Journal of Neuroscience*, *34*(27), 8988–8998. https://doi.org/10.1523/JNEUROSCI.0261-14.2014

Compton, R. J., Gearinger, D., & Wild, H. (2019). The wandering mind oscillates: EEG alpha power is enhanced during moments of mind-wandering. *Cognitive, Affective and Behavioral Neuroscience*, *19*(5), 1184–1191. https://doi.org/10.3758/s13415-019-00745-9

D'Andola, M., Rebollo, B., Casali, A. G., Weinert, J. F., Pigorini, A., Villa, R., Massimini, M., & Sanchez-Vives, M. V. (2018). Bistability, causality, and complexity in cortical networks: An in vitro perturbational study. *Cerebral Cortex*, *28*(7), 2233–2242. https://doi.org/10.1093/cercor/bhx122

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *13*, 9–21. http://dx.doi.org/10.1016/j.jneumeth.2003.10.009

Dixon, M. L., Fox, K. C. R., & Christoff, K. (2014). A framework for understanding the relationship between externally and internally directed cognition. *Neuropsychologia*, *62*, 321–330. https://doi.org/10.1016/j.neuropsychologia.2014.05.024

Dolan, D., Jensen, H. J., Mediano, P. A. M., Molina-Solana, M., Rajpal, H., Rosas, F., & Sloboda, J. A. (2018). The improvisational state of mind: A multidisciplinary study of an improvisatory approach to classical music repertoire performance. *Frontiers in Psychology*, *9*(SEP). https://doi.org/10.3389/fpsyg.2018.01341

Duprez, J., Stokkermans, M., Drijvers, L., & Cohen, M. X. (2021). Synchronization between keyboard typing and neural oscillations. *Journal of Cognitive Neuroscience*, *33*(5), 887–901. https://doi.org/10.1162/jocn_a_01692

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Forster, S., & Lavie, N. (2014). Distracted by your mind? Individual differences in distractibility predict mind wandering. *Journal of Experimental Psychology: Learning Memory and Cognition*, *40*(1), 251–260. https://doi.org/10.1037/a0034108

Fox, K. C. R., Andrews-Hanna, J. R., Mills, C., Dixon, M. L., Markovic, J., Thompson, E., & Christoff, K. (2018). Affective neuroscience of self-generated thought. *Annals of the New York Academy of Sciences*, *1426*(1), 25–51. https://doi.org/10.1111/nyas.13740

Fox, K. C. R., Spreng, R. N., Ellamil, M., Andrews-hanna, J. R., & Christoff, K. (2015). The wandering brain: Meta-analysis of functional neuroimaging studies of mind-wandering and related spontaneous thought processes. *NeuroImage*. https://doi.org/10.1016/j.neuroimage.2015.02.039

Foxe, J. J., & Snyder, A. C. (2011). The Role of Alpha-Band Brain Oscillations as a Sensory Suppression Mechanism during Selective Attention. *Frontiers in Psychology*, *2*. https://doi.org/10.3389/fpsyg.2011.00154

Franklin, M. S., Smallwood, J., & Schooler, J. W. (2011). Catching the mind in flight: Using behavioral indices to detect mindless reading in real time. *Psychonomic Bulletin and Review*, *18*(5), 992–997. https://doi.org/10.3758/s13423-011-0109-6

Fries, P. (2005). A mechanism for cognitive dynamics: Neuronal communication through neuronal coherence. *Trends in Cognitive Sciences*, *9*(10), 474–480. https://doi.org/10.1016/j.tics.2005.08.011

Frömer, R., Maier, M., & Abdel Rahman, R. (2018). Group-level EEG-processing pipeline for flexible single trial-based analyses including linear mixed models. *Frontiers in Neuroscience*, *12*(FEB), 1–15. https://doi.org/10.3389/fnins.2018.00048

Geden, M., Staicu, A.-M., & Feng, J. (2018). Reduced Target Facilitation and Increased Distractor Suppression During Mind Wandering. *Experimental Psychology*, *65*(6), 345–352. https://doi.org/10.1027/1618-3169/a000417

Girn, M., Mills, C., Laycock, E., Ellamil, M., Ward, L., & Christoff, K. (2017). Neural Dynamics of Spontaneous Thought: An Electroencephalographic Study. *Augmented Cognition. Neurocognition and Machine Learning*, *10284*, 28–44. https://doi.org/10.1007/978-3-319-58628-1

Girn, M., Mills, C., Roseman, L., Carhart-Harris, R. L., & Christoff, K. (2020). Updating the dynamic framework of thought: Creativity and psychedelics. *NeuroImage*, *213*(September 2019), 116726. https://doi.org/10.1016/j.neuroimage.2020.116726

Golesorkhi, M., Gomez-Pilar, J., Tumati, S., Fraser, M., & Northoff, G. (2021). Temporal hierarchy of intrinsic neural timescales converges with spatial core-periphery organization. *Communications Biology*, *4*(1), 1–14. https://doi.org/10.1038/s42003-021-01785-z

Golesorkhi, M., Gomez-Pilar, J., Zilio, F., Berberian, N., Wolff, A., Yagoub, M. C. E., & Northoff, G. (2021). The brain and its time: Intrinsic neural timescales are key for input processing. *Communications Biology*, *4*(1), 970. https://doi.org/10.1038/s42003-021-02483-6

Gomez-Pilar, J., Poza, J., Gómez, C., Northoff, G., Lubeiro, A., Cea-Cañas, B. B., Molina, V., & Hornero, R. (2018). Altered predictive capability of the brain network EEG model in schizophrenia during cognition. *Schizophrenia Research*, *201*, 120–129. https://doi.org/10.1016/j.schres.2018.04.043

Gonçalves, Ó. F., Carvalho, S., Mendes, A. J., Leite, J., & Boggio, P. S. (2018). Neuromodulating Attention and Mind-Wandering Processes with a Single Session Real Time EEG. *Applied Psychophysiology Biofeedback*, *43*(2), 143–151. https://doi.org/10.1007/s10484-018-9394-4

Gonçalves, Ó. F., Rêgo, G., Conde, T., Leite, J., Carvalho, S., Lapenta, O. M., & Boggio, P. S. (2018). Mind Wandering and Task-Focused Attention: ERP Correlates. *Scientific Reports*, *8*(1), 1–14. https://doi.org/10.1038/s41598-018-26028-w

Gosseries, O., Schnakers C Fau - Ledoux, D., Ledoux D Fau - Vanhaudenhuyse, A., Vanhaudenhuyse A Fau - Bruno, M.-A., Bruno Ma Fau - Demertzi, A., Demertzi A Fau - Noirhomme, Q., Noirhomme Q Fau - Lehembre, R., Lehembre R Fau - Damas, P., Damas P Fau - Goldman, S., Goldman S Fau - Peeters, E., Peeters E Fau - Moonen, G., Moonen G Fau - Laureys, S., & Laureys, S. (2011). Automated EEG entropy measurements in coma, vegetative state/unresponsive wakefulness syndrome and minimally conscious state. *Functional Neurology*, *26*(1), 25–30.

Grandy, T. H., Werkle-Bergner, M., Chicherio, C., Schmiedek, F., Lövdén, M., & Lindenberger, U. (2013). Peak individual alpha frequency qualifies as a stable neurophysiological trait marker in healthy younger and older adults. *Psychophysiology*, *50*(6), 570–582. https://doi.org/10.1111/psyp.12043

Groot, J. M., Csifcsák, G., Wientjes, S., Forstmann, B. U., & Mittner, M. (2022). Catching wandering minds with tapping fingers: Neural and behavioral insights into task-unrelated cognition. *Cerebral Cortex*, *32*(20), 4447–4463. https://doi.org/10.1093/cercor/bhab494

Gulbinaite, R., Van Viegen, T., Wieling, M., Cohen, M. X., & Vanrullen, R. (2017). Individual alpha peak frequency predicts 10 hz flicker effects on selective attention. *Journal of Neuroscience*, *37*(42), 10173–10184. https://doi.org/10.1523/JNEUROSCI.1163-17.2017

Handy, T. C., & Kam, J. W. Y. (2015). Mind Wandering and Selective Attention to the External

World External Disengagement: Early Versus Late Selection. *Canadian Journal of Experimental Psychology*, *69*(2), 183–189.

Hanslmayr, S., Klimesch, W., Sauseng, P., Gruber, W., Doppelmayr, M., Freunberger, R., Pecherstorfer, T., & Birbaumer, N. (2006). Alpha Phase Reset Contributes to the Generation of ERPs. *Cerebral Cortex*, *17*(1), 1–8. https://doi.org/10.1093/cercor/bhj129

Hayes, A. F. (2012). *PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling*. University of Kansas, KS.

H.-C., H., & Jansen, B. H. (1985). Eeg waveform analysis by means of dynamic time-warping. *Bio-Medical Computing*, *17*, 135–144.

He, B. J. (2013). Spontaneous and task-evoked brain activity negatively interact. *Journal of Neuroscience*, *33*(11), 4672–4682. https://doi.org/10.1523/JNEUROSCI.2922-12.2013

Hester, R., Foxe, J. J., Molholm, S., Shpaner, M., & Garavan, H. (2005). Neural mechanisms involved in error processing: A comparison of errors made with and without awareness. *NeuroImage*, *27*(3), 602–608. https://doi.org/10.1016/j.neuroimage.2005.04.035

Ho, N. S. P., Poerio, G., Konu, D., Turnbull, A., Sormaz, M., Leech, R., Bernhardt, B., Jefferies, E., & Smallwood, J. (2020). Facing up to the wandering mind: Patterns of off-task laboratory thought are associated with stronger neural recruitment of right fusiform cortex while processing facial stimuli. *NeuroImage*, *214*. https://doi.org/10.1016/j.neuroimage.2020.116765

Hua, J., Wolff, A., Zhang, J., Yao, L., Zang, Y., Luo, J., Ge, X., Liu, C., & Northoff, G. (2022). Alpha and theta peak frequency track on- and off-thoughts. *Communications Biology*, *5*(1), 1–13. https://doi.org/10.1038/s42003-022-03146-w

Huang, Z., Zhang, J., Longtin, A., Dumont, G., Duncan, N. W., Pokorny, J., Qin, P., Dai, R., Ferri, F., Weng, X., & Northoff, G. (2017). Is There a Nonadditive Interaction Between Spontaneous and Evoked Activity? Phase-Dependence and Its Relation to the Temporal Structure of Scale-Free Brain Activity. *Cerebral Cortex (New York, N.Y.: 1991)*, *27*(2), 1037–1059. https://doi.org/10.1093/cercor/bhv288

Huber, D. E., Tian, X., Curran, T., O'Reilly, R. C., & Woroch, B. (2008). The dynamics of integration and separation: ERP, MEG, and neural network studies of immediate repetition effects. *Journal of Experimental Psychology: Human Perception and Performance*, *34*(6), 1389–1416. https://doi.org/10.1037/a0013625

Hudetz, A. G., Liu, X., & Pillay, S. (2015). Dynamic repertoire of intrinsic brain states is reduced in propofol-induced unconsciousness. *Brain Connectivity*, *5*(1), 10–22.

https://doi.org/10.1089/brain.2014.0230

Irving, Z. C. (2016). Mind-wandering is unguided attention: Accounting for the “purposeful” wanderer. *Philosophical Studies*, *173*(2), 547–571. https://doi.org/10.1007/s11098-015-0506-1

Jensen, O., & Mazaheri, A. (2010). Shaping Functional Architecture by Oscillatory Alpha Activity: Gating by Inhibition. *Frontiers in Human Neuroscience*, *4*. https://doi.org/10.3389/fnhum.2010.00186

Jia, H., Li, H., & Yu, D. (2017). The relationship between ERP components and EEG spatial complexity in a visual Go / Nogo task. *Journal of Neurophysiology*, *117*(1), 275–283. https://doi.org/10.1152/jn.00363.2016

Jin, C. Y., Borst, J. P., & Vugt, M. K. V. (2019). Predicting task-general mind-wandering with EEG. *Cognitive, Affective, & Behavioral Neuroscience*, *19*(4), 1059–1073. https://doi.org/10.3758/s13415-019-00707-1.

Kajimura, S., & Nomura, M. (2015). Decreasing propensity to mind-wander with transcranial direct current stimulation. *Neuropsychologia*, *75*, 533–537. https://doi.org/10.1016/j.neuropsychologia.2015.07.013

Kam, J. W. Y., & Handy, T. C. (2013). The neurocognitive consequences of the wandering mind: A mechanistic account of sensory-motor decoupling. *Frontiers in Psychology*, *4*(October), 1–13. https://doi.org/10.3389/fpsyg.2013.00725

Kam, J. W. Y., Mittner, M., & Knight, R. T. (2022). Mind-wandering: Mechanistic insights from lesion, tDCS, and iEEG. *Trends in Cognitive Sciences*, *26*(3), 268–282. https://doi.org/10.1016/j.tics.2021.12.005

Karapanagiotidis, T., Vidaurre, D., Quinn, A. J., Vatansever, D., Poerio, G. L., Jefferies, E., Margulies, D. S., Nichols, T. E., Woolrich, M. W., & Smallwood, J. (2018). *Neural dynamics at rest associated with patterns of ongoing thought*. Neuroscience. https://doi.org/10.1101/454371

Kiebel, S. J., Daunizeau, J., & Friston, K. J. (2008). A Hierarchy of Time-Scales and the Brain. *PLoS Computational Biology*, *4*(11), e1000209. https://doi.org/10.1371/journal.pcbi.1000209

Kliger Amrani, A., & Zion Golumbic, E. (2020). Testing the stability of ‘Default’ motor and auditory-perceptual rhythms–A replication failure dataset. *Data in Brief*, *32*, 106044. https://doi.org/10.1016/j.dib.2020.106044

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Knyazev, G. G., Slobodskoj-Plusnin, J. Y., Bocharov, A. V., & Pylkova, L. V. (2011). The default mode network and EEG alpha oscillations: An independent component analysis. *Brain Research*, *1402*, 67–79.

Kolvoort, I. R., Wainio-Theberge, S., Wolff, A., & Northoff, G. (2020). Temporal integration as "common currency" of brain and self-scale-free activity in resting-state EEG correlates with temporal delay effects on self-relatedness. *Human Brain Mapping*, *41*(15), 4355–4374. https://doi.org/10.1002/hbm.25129

Konu, D., Turnbull, A., Karapanagiotidis, T., Wang, H. T., Brown, L. R., Jefferies, E., & Smallwood, J. (2020). A role for the ventromedial prefrontal cortex in self-generated episodic social cognition. *NeuroImage*, *218*(March), 116977. https://doi.org/10.1016/j.neuroimage.2020.116977

Kopell, N., Kramer, M. A., Malerba, P., & Whittington, M. A. (2010). Are different rhythms good for different functions? *Frontiers in Human Neuroscience*, *4*(November), 1–9. https://doi.org/10.3389/fnhum.2010.00187

Kucyi, A. (2018). Just a thought: How mind-wandering is represented in dynamic brain connectivity. *NeuroImage*, *180*, 505–514. https://doi.org/10.1016/j.neuroimage.2017.07.001

Kucyi, A., Esterman, M., Capella, J., Green, A., Uchida, M., Biederman, J., Gabrieli, J. D. E., Valera, E. M., & Whitfield-Gabrieli, S. (2021). Prediction of stimulus-independent and task-unrelated thought from functional brain networks. *Nature Communications*, *12*(1), 1793. https://doi.org/10.1038/s41467-021-22027-0

Kucyi, A., Esterman, M., Riley, C. S., & Valera, E. M. (2016). Spontaneous default network activity reflects behavioral variability independent of mind-wandering. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(48), 13899–13904. https://doi.org/10.1073/pnas.1611743113

Kucyi, A., Hove, M. J., Esterman, M., Hutchison, R. M., & Valera, E. M. (2017). Dynamic Brain Network Correlates of Spontaneous Fluctuations in Attention. *Cerebral Cortex (New York, N.Y. : 1991)*, *27*(3), 1831–1840. https://doi.org/10.1093/cercor/bhw029

Kucyi, A., Tambini, A., Sadaghiani, S., Keilholz, S., & Cohen, J. R. (2018). Spontaneous cognitive processes and the behavioral validation of time-varying brain connectivity Aaron. *Network Neuroscience*, *2*(4), 397–417. https://doi.org/10.1162/NETN

Kuehni, R. G. (2009). Variability in estimation of suprathreshold small color differences. *Color Research & Application*, *34*(5), 367–374. https://doi.org/10.1002/col.20522

Kutz, D. F., Fröhlich, S., Rudisch, J., Müller, K., & Voelcker-Rehage, C. (2022). Finger Tapping as a Biomarker to Classify Cognitive Status in 80+-Year-Olds. *Journal of Personalized Medicine*, *12*(2). https://doi.org/10.3390/jpm12020286

Lachaux, J.-P., Rodriguez, E., Martinerie, J., & Varela, F. J. (1999). Measuring phase synchrony in brain signals. *Human Brain Mapping*, *8*(4), 194–208. https://doi.org/10.1002/(SICI)1097-0193(1999)8:4%253C194::AID-HBM4%253E3.0.CO;2-C

Langdon, A. J., & Chaudhuri, R. (2021). An evolving perspective on the dynamic brain: Notes from the Brain Conference on *Dynamics of the brain: Temporal aspects of computation*. *European Journal of Neuroscience*, *53*(11), 3511–3524. https://doi.org/10.1111/ejn.14963

Lansbergen, M. M., Arns, M., Van Dongen-Boomsma, M., Spronk, D., & Buitelaar, J. K. (2011). The increase in theta/beta ratio on resting-state EEG in boys with attention-deficit/hyperactivity disorder is mediated by slow alpha peak frequency. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *35*(1), 47–52. https://doi.org/10.1016/j.pnpbp.2010.08.004

Lau, Z. J., Pham, T., Chen, S. H. A., & Makowski, D. (2022). Brain entropy, fractal dimensions and predictability: A review of complexity measures for EEG in healthy and neuropsychiatric populations. *European Journal of Neuroscience*, *56*(7), 5047–5069. https://doi.org/10.1111/ejn.15800

Lechner, S., & Northoff, G. (2023). Temporal imprecision and phase instability in schizophrenia resting state EEG. *Asian Journal of Psychiatry*, *86*, 103654. https://doi.org/10.1016/j.ajp.2023.103654

Liu, Q., Ma, L., Fan, S.-Z., Abbod, M. F., & Shieh, J.-S. (2018). Sample entropy analysis for the estimating depth of anaesthesia through human EEG signal at different levels of unconsciousness during surgeries. *PeerJ*, *6*, e4817. https://doi.org/10.7717/peerj.4817

Long, Z., Northoff, G., & Fu, X. (2025). Task difficulty modulates the effect of mind wandering on phase dynamics. *Proceedings of the National Academy of Sciences*, *122*(22), e2416387122. https://doi.org/10.1073/pnas.2416387122

López, M. E., Pusil, S., Pereda, E., Maestú, F., & Barceló, F. (2019). Dynamic low frequency EEG phase synchronization patterns during proactive control of task switching. *NeuroImage*, *186*, 70–82. https://doi.org/10.1016/j.neuroimage.2018.10.068

Luo, M., Zhang, H., & Luo, H. (2024). *Reactivated past decisions repel early sensory processing and attract late decision-making*. https://doi.org/10.1101/2024.02.26.582221

Marchetti, I., Koster, E. H. W., Klinger, E., & Alloy, L. B. (2016). Spontaneous thought and vulnerability to mood disorders: The dark side of the wandering mind. *Clinical Psychological*

Science, *4*(5), 835–857. https://doi.org/10.1177/2167702615622383

Margulies, D. S., Ghosh, S. S., Goulas, A., Falkiewicz, M., Huntenburg, J. M., Langs, G., Bezgin, G., Eickhoff, S. B., Castellanos, F. X., Petrides, M., Jefferies, E., & Smallwood, J. (2016). Situating the default-mode network along a principal gradient of macroscale cortical organization. *Proceedings of the National Academy of Sciences*, *113*(44), 12574–12579. https://doi.org/10.1073/pnas.1608282113

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods*, *164*(1), 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024

Martinon, L. M., Smallwood, J., McGann, D., Hamilton, C., & Riby, L. M. (2019). The disentanglement of the neural and experiential complexity of self-generated thoughts: A users guide to combining experience sampling with neuroimaging data. *NeuroImage*, *192*(September 2018), 15–25. https://doi.org/10.1016/j.neuroimage.2019.02.034

Menon, V. (2023). 20 years of the default mode network: A review and synthesis. *Neuron*, *111*(16), 2469–2487. https://doi.org/10.1016/j.neuron.2023.04.023

Mierau, A., Klimesch, W., & Lefebvre, J. (2017). State-dependent alpha peak frequency shifts: Experimental evidence, potential mechanisms and functional implications. *Neuroscience*, *360*, 146–154. https://doi.org/10.1016/j.neuroscience.2017.07.037

Mills, C., Porter, A. R., Andrews-Hanna, J. R., Christoff, K., & Colby, A. (2021). How Task-Unrelated and Freely Moving Thought Relate to Affect: Evidence for Dissociable Patterns in Everyday Life. *Emotion*, *21*(5), 1029–1040. https://doi.org/10.1037/emo0000849

Mills, C., Raffaelli, Q., Irving, Z. C., Stan, D., & Christoff, K. (2018). Is an off-task mind a freely-moving mind? Examining the relationship between different dimensions of thought. *Consciousness and Cognition*, *58*, 20–33. https://doi.org/10.1016/j.concog.2017.10.003

Moran, R. J., Campo, P., Maestu, F., Reilly, R. B., Dolan, R. J., & Strange, B. A. (2010). Peak frequency in the theta and alpha bands correlates with human working memory capacity. *Frontiers in Human Neuroscience*, *4*(November), 1–12. https://doi.org/10.3389/fnhum.2010.00200

Murphy, C., Poerio, G., Sormaz, M., Wang, H. T., Vatansever, D., Allen, M., Margulies, D. S., Jefferies, E., & Smallwood, J. (2019). Hello, is that me you are looking for? A reexamination of the role of the DMN in social and self relevant aspects of off-task thought. *PLoS ONE*, *14*(11), 1–19. https://doi.org/10.1371/journal.pone.0216182

Murphy, C., Wang, H. T., Konu, D., Lowndes, R., Margulies, D. S., Jefferies, E., & Smallwood, J.

(2019). Modes of operation: A topographic neural gradient supporting stimulus dependent and independent cognition. *NeuroImage*, *186*(November 2018), 487–496. https://doi.org/10.1016/j.neuroimage.2018.11.009

Murray, J. D., Bernacchia, A., Freedman, D. J., Romo, R., Wallis, J. D., Cai, X., Padoa-Schioppa, C., Pasternak, T., Seo, H., Lee, D., & Wang, X. J. (2014). A hierarchy of intrinsic timescales across primate cortex. *Nature Neuroscience*, *17*(12), 1661–1663. https://doi.org/10.1038/nn.3862

Nakatani, H., Kawasaki, M., Kitajo, K., & Yamaguchi, Y. (2021). Frequency-dependent effects of EEG phase resetting on reaction time. *Neuroscience Research*, *172*, 51–62. https://doi.org/10.1016/j.neures.2021.05.006

Northoff, G. (2018). *The spontaneous brain: From the mind-body to the world-brain problem*. MIT Press.

Northoff, G. (2024). *From Brain Dynamics to the Mind: Spatiotemporal Neuroscience*. Academic Press.

Northoff, G., Buccellato, A., & Zilio, F. (2024). Connecting brain and mind through temporo-spatial dynamics: Towards a theory of common currency. *Physics of Life Reviews*, *52*, 29–43. https://doi.org/10.1016/j.plrev.2024.11.012

Northoff, G., Duncan, N. W., & Hayes, D. J. (2010). The brain and its resting state activity—Experimental and methodological implications. *Progress in Neurobiology*, *92*(4), 593–600. https://doi.org/10.1016/j.pneurobio.2010.09.002

Northoff, G., & Huang, Z. (2017). How do the brain's time and space mediate consciousness and its different dimensions? Temporo-spatial theory of consciousness (TTC). *Neuroscience and Biobehavioral Reviews*, *80*, 630–645. https://doi.org/10.1016/j.neubiorev.2017.07.013

Northoff, G., Klar, P., Bein, M., & Safron, A. (2023). As without, so within: How the brain's temporo-spatial alignment to the environment shapes consciousness. *Interface Focus*, *13*(3), 20220076. https://doi.org/10.1098/rsfs.2022.0076

Northoff, G., Vatansever, D., Scalabrini, A., & Stamatakis, E. A. (2022). Ongoing Brain Activity and Its Role in Cognition: Dual versus Baseline Models. *The Neuroscientist*, 1–28. https://doi.org/10.1177/10738584221081752

Northoff, G., Wainio-Theberge, S., & Evers, K. (2020a). Is temporo-spatial dynamics the "common currency" of brain and mind? In Quest of "Spatiotemporal Neuroscience." *Physics of Life Reviews*, *1*, 1–21. https://doi.org/10.1016/j.plrev.2019.05.002

Northoff, G., Wainio-Theberge, S., & Evers, K. (2020b). Spatiotemporal neuroscience – what is it and why we need it. *Physics of Life Reviews*, *33*, 78–87. https://doi.org/10.1016/j.plrev.2020.06.005

Northoff, G., Zilio, F., & Zhang, J. (2024). Beyond task response—Pre-stimulus activity modulates contents of consciousness. *Physics of Life Reviews*, *49*, 19–37. https://doi.org/10.1016/j.plrev.2024.03.002

Northoff, G., Zilio, F., & Zhang, J. (2025). From pre-stimulus activity to the contents of consciousness – A spatiotemporal view: Reply to comments on "Beyond task response-Pre-stimulus activity modulates contents of consciousness." *Physics of Life Reviews*, *53*, 76–90. https://doi.org/10.1016/j.plrev.2025.02.006

Palva, J. M., & Palva, S. (2018). Functional integration across oscillation frequencies by cross-frequency phase synchronization. *European Journal of Neuroscience*, *48*(7), 2399–2406. https://doi.org/10.1111/ejn.13767

Palva, S., & Palva, J. M. (2007). New vistas for α-frequency band oscillations. *Trends in Neurosciences*, *30*(4), 150–158. https://doi.org/10.1016/j.tins.2007.02.001

Pedersen, M., Omidvarnia, A., Walz, J. M., Zalesky, A., & Jackson, G. D. (2017). Spontaneous brain network activity: Analysis of its temporal complexity. *Network Neuroscience*, *1*(2), 100–115. https://doi.org/10.1162/NETN_a_00006

Petilli, M. A., Trisolini, D. C., & Daini, R. (2018). Sustained-Paced Finger Tapping: A Novel Approach to Measure Internal Sustained Attention. *Frontiers in Psychology*, *9*, 881. https://doi.org/10.3389/fpsyg.2018.00881

Polanco-Martinez, J., M., Medina-Elizalde, M., A., Goni, M., Fernanda,Sanchez, & Mudelsee, M. (2019). BINCOR: An R package for Estimating the Correlation between Two Unevenly Spaced Time Series. *The R Journal*, *11*(1), 170. https://doi.org/10.32614/RJ-2019-035

Polich, J. (2003). Theoretical Overview of P3a and P3b. In *Detection of Change*. Springer. https://doi.org/10.1007/978-1-4615-0294-4_5

Pöppel, E. (2009). Pre-semantically defined temporal windows for cognitive processing. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1525), 1887–1896. https://doi.org/10.1098/rstb.2009.0015

Ramsay, I. S., Lynn, P. A., Schermitzler, B., & Sponheim, S. R. (2021). Individual alpha peak frequency is slower in schizophrenia and related to deficits in visual perception and cognition. *Scientific Reports*, *11*(1), 17852. https://doi.org/10.1038/s41598-021-97303-6

Rapela, J., Westerfield, M., & Townsend, J. (2018). A New Foreperiod Effect on Intertrial Phase Coherence. Part I: Existence and Behavioral Relevance. *Neural Computation*, *30*(9), 2348–2383. https://doi.org/10.1162/neco_a_01109

Rathee, S., Bhatia, D., Punia, V., & Singh, R. (2020). Peak Alpha Frequency in Relation to Cognitive Performance. *Journal of Neurosciences in Rural Practice*, *11*, 416–419. https://doi.org/10.1055/s-0040-1712585

Raut, R. V., Snyder, A. Z., & Raichle, M. E. (2020). Hierarchical dynamics as a macroscopic organizing principle of the human brain. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(34), 20890–20897. https://doi.org/10.1073/pnas.2003383117

Rodriguez-Larios, J., & Alaerts, K. (2019). Tracking Transient Changes in the Neural Frequency Architecture: Harmonic Relationships between Theta and Alpha Peaks Facilitate Cognitive Performance. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *39*(32), 6291–6298. https://doi.org/10.1523/JNEUROSCI.2919-18.2019

Rose, D., Cameron, D. J., Lovatt, P. J., Grahn, J. A., & Annett, L. E. (2020). Comparison of spontaneous motor tempo during finger tapping, toe tapping and stepping on the spot in people with and without parkinson's disease. *Journal of Movement Disorders*, *13*(1), 47–56. https://doi.org/10.14802/jmd.19043

Rostami, S., Borjali, A., Eskandari, H., Rostami, R., Scalabrini, A., & Northoff, G. (2022). Slow and Powerless Thought Dynamic Relates to Brooding in Unipolar and Bipolar Depression. *Psychopathology*, *55*(5), 258–272. https://doi.org/10.1159/000523944

Sarasso, S., Boly, M., Napolitani, M., Gosseries, O., Charland-Verville, V., Casarotto, S., Rosanova, M., Casali, A. G., Brichant, J.-F., Boveroux, P., Rex, S., Tononi, G., Laureys, S., & Massimini, M. (2015). Consciousness and Complexity during Unresponsiveness Induced by Propofol, Xenon, and Ketamine. *Current Biology*, *25*(23), 3099–3105. https://doi.org/10.1016/j.cub.2015.10.014

Saxe, G. N., Calderone, D., & Morales, L. J. (2018). Brain entropy and human intelligence: A resting-state fMRI study. *PLOS ONE*, *13*(2), e0191582. https://doi.org/10.1371/journal.pone.0191582

Scalabrini, A., Huang, Z., Mucci, C., Perrucci, M. G., Ferretti, A., Fossati, A., Romani, G. L., Northoff, G., & Ebisch, S. J. H. (2017). How spontaneous brain activity and narcissistic features shape social interaction. *Scientific Reports*, *Mi*, 1–12. https://doi.org/10.1038/s41598-017-10389-9

Scalabrini, A., Schimmenti, A., De Amicis, M., Porcelli, P., Benedetti, F., Mucci, C., & Northoff, G. (2022). The self and its internal thought: In search for a psychological baseline. *Consciousness and Cognition*, *97*(November 2021), 103244. https://doi.org/10.1016/j.concog.2021.103244

Schacter, D. L., Addis, D. R., Hassabis, D., Martin, V. C., Spreng, R. N., & Szpunar, K. K. (2012). The Future of Memory: Remembering, Imagining, and the Brain. *Neuron*, *76*(4), 677–694. https://doi.org/10.1016/j.neuron.2012.11.001

Schooler, J. W., Smallwood, J., Christoff, K., Handy, T. C., Reichle, E. D., & Sayette, M. A. (2011). Meta-awareness, perceptual decoupling and the wandering mind. *Trends in Cognitive Sciences*, *15*(7), 319–326. https://doi.org/10.1016/j.tics.2011.05.006

Seli, P., Kane, M. J., Metzinger, T., Smallwood, J., Schacter, D. L., Maillet, D., Schooler, J. W., & Smilek, D. (2018). The family-resemblances framework for mind-wandering remains well clad. *Trends in Cognitive Sciences*, *22*(11), 959–961.

Seli, P., Kane, M. J., Smallwood, J., Schacter, D. L., Maillet, D., Schooler, J. W., & Smilek, D. (2018). Mind-Wandering as a Natural Kind: A Family-Resemblances View. *Trends in Cognitive Sciences*, *22*(6), 479–490. https://doi.org/10.1016/j.tics.2018.03.010

Sharma, S., Sasidharan, A., Marigowda, V., Vijay, M., Sharma, S., Mukundan, C. S., Pandit, L., & Masthi, N. R. R. (2020). Indian classical music with incremental variation in tempo and octave promotes better anxiety reduction and controlled mind wandering—A randomised controlled EEG study. *Explore*, *000*, 1–7. https://doi.org/10.1016/j.explore.2020.02.013

Sitt, J. D., King, J. R., El Karoui, I., Rohaut, B., Faugeras, F., Gramfort, A., Cohen, L., Sigman, M., Dehaene, S., & Naccache, L. (2014). Large scale screening of neural signatures of consciousness in patients in a vegetative or minimally conscious state. *Brain*, *137*(8), 2258–2270. https://doi.org/10.1093/brain/awu141

Smallwood, J. (2013). Distinguishing how from why the mind wanders: A process-occurrence framework for self-generated mental activity. *Psychological Bulletin*, *139*(3), 519–535. https://doi.org/10.1037/a0030010

Smallwood, J., Beach, E., Schooler, J. W., & Handy, T. C. (2008). Going AWOL in the brain: Mind wandering reduces cortical analysis of external events. *Journal of Cognitive Neuroscience*, *20*(3), 458–469. https://doi.org/10.1162/jocn.2008.20037

Smallwood, J., Bernhardt, B. C., Leech, R., Bzdok, D., Jefferies, E., & Margulies, D. S. (2021). The default mode network in cognition: A topographical perspective. *Nature Reviews Neuroscience*, *22*(8), 503–513. https://doi.org/10.1038/s41583-021-00474-4

Smallwood, J., Fitzgerald, A., Miles, L. K., & Phillips, L. H. (2009). Shifting Moods, Wandering Minds: Negative Moods Lead the Mind to Wander. *Emotion*, *9*(2), 271–276. https://doi.org/10.1037/a0014855

Smallwood, J., & Schooler, J. (2015). The Science of Mind Wandering: Empirically Navigating the Stream of Consciousness. *Annual Review of Psychology*, *66*, 487–518. https://doi.org/10.1146/annurev-psych-010814-015331

Smallwood, J., & Schooler, J. W. (2006). The restless mind. *Psychological Bulletin*, *132*(6), 946–958. https://doi.org/10.1037/0033-2909.132.6.946

Smallwood, J., Tipper, C., Brown, K., Baird, B., Engen, H., Michaels, J. R., Grafton, S., & Schooler, J. W. (2013). Escaping the here and now: Evidence for a role of the default mode network in perceptually decoupled thought. *NeuroImage*, *69*, 120–125. https://doi.org/10.1016/j.neuroimage.2012.12.012

Smallwood, J., Turnbull, A., Wang, H. ting, Ho, N. S. P., Poerio, G. L., Karapanagiotidis, T., Konu, D., Mckeown, B., Zhang, M., Murphy, C., Vatansever, D., Bzdok, D., Konishi, M., Leech, R., Seli, P., Schooler, J. W., Bernhardt, B., Margulies, D. S., & Jefferies, E. (2021). The neural correlates of ongoing conscious thought. *iScience*, *24*(3), 1–15. https://doi.org/10.1016/j.isci.2021.102132

Sormaz, M., Murphy, C., Wang, H., Hymers, M., Karapanagiotidis, T., Poerio, G., Margulies, D. S., Jefferies, E., & Smallwood, J. (2018). Default mode network can support the level of detail in experience during active task states. *Proceedings of the National Academy of Sciences*, *115*(37), 9318–9323. https://doi.org/10.1073/pnas.1721259115

Stawarczyk, D., Cassol, H., & D’Argembeau, A. (2013). Phenomenology of future-oriented mind-wandering episodes. *Frontiers in Psychology*, *4*(JUL), 1–12. https://doi.org/10.3389/fpsyg.2013.00425

Stawarczyk, D., François, C., Wertz, J., & D’Argembeau, A. (2020). Drowsiness or mind-wandering? Fluctuations in ocular parameters during attentional lapses. *Biological Psychology*, *156*. https://doi.org/10.1016/j.biopsycho.2020.107950

Tagliazucchi, E., & Laufs, H. (2014). Article Decoding Wakefulness Levels from Typical fMRI Resting-State Data Reveals Reliable Drifts between Wakefulness and Sleep. *Neuron*, *82*(3), 695–708. https://doi.org/10.1016/j.neuron.2014.03.020

Taheri-Araghi, S., Bradde, S., Sauls, J. T., Hill, N. S., Levin, P. A., Paulsson, J., Vergassola, M., & Jun, S. (2015). Cell-Size Control and Homeostasis in Bacteria. *Current Biology*, *25*(3), 385–391. https://doi.org/10.1016/j.cub.2014.12.009

Taylor, P., Hobbs, J. N., Burroni, J., & Siegelmann, H. T. (2015). The global landscape of cognition: Hierarchical aggregation as an organizational principle of human cortical networks and functions. *Scientific Reports*, *5*(June), 1–18. https://doi.org/10.1038/srep18112

Theiler, J., Eubank, S., Longtin, A., Galdrikian, B., & Doyne Farmer, J. (1992). Testing for nonlinearity in time series: The method of surrogate data. *Physica D: Nonlinear Phenomena*, *58*(1–4), 77–94. https://doi.org/10.1016/0167-2789(92)90102-S

Thönes, S., & Stocker, K. (2019). A standard conceptual framework for the study of subjective time. *Consciousness and Cognition*, *71*, 114–122. https://doi.org/10.1016/j.concog.2019.04.004

Tian, X., & Huber, D. E. (2008). Measures of Spatial Similarity and Response Magnitude in MEG and Scalp EEG. *Brain Topography*, *20*(3), 131–141. https://doi.org/10.1007/s10548-007-0040-3

Turnbull, A., Wang, H. T., Murphy, C., Ho, N. S. P., Wang, X., Sormaz, M., Karapanagiotidis, T., Leech, R. M., Bernhardt, B., Margulies, D. S., Vatansever, D., Jefferies, E., & Smallwood, J. (2019). Left dorsolateral prefrontal cortex supports context-dependent prioritisation of off-task thought. *Nature Communications*, *10*(1). https://doi.org/10.1038/s41467-019-11764-y

Turnbull, A., Wang, H. T., Schooler, J. W., Jefferies, E., Margulies, D. S., & Smallwood, J. (2019). The ebb and flow of attention: Between-subject variation in intrinsic connectivity and cognition associated with the dynamics of ongoing experience. *NeuroImage*, *185*, 286–299. https://doi.org/10.1016/j.neuroimage.2018.09.069

Van Diepen, R. M., & Mazaheri, A. (2018). The Caveats of observing Inter-Trial Phase-Coherence in Cognitive Neuroscience. *Scientific Reports*, *8*(1), 2990. https://doi.org/10.1038/s41598-018-20423-z

van Son, D., De Blasio, F. M., Fogarty, J. S., Angelidis, A., Barry, R. J., & Putman, P. (2019). Frontal EEG theta/beta ratio during mind wandering episodes. *Biological Psychology*, *140*, 19–27. https://doi.org/10.1016/j.biopsycho.2018.11.003

van Son, D., de Rover, M., De Blasio, F. M., van der Does, W., Barry, R. J., & Putman, P. (2019). Electroencephalography theta/beta ratio covaries with mind wandering and functional connectivity in the executive control network. *Annals of the New York Academy of Sciences*, *1452*(1), 52–64. https://doi.org/10.1111/nyas.14180

Vanhaudenhuyse, A., Demertzi, A., Schabus, M., Noirhomme, Q., Bredart, S., Boly, M., Phillips, C., Soddu, A., Luxen, A., Moonen, G., & Laureys, S. (2011). Two distinct neuronal networks mediate the awareness of environment and of self. *Journal of Cognitive Neuroscience*, *23*(3), 570–578. https://doi.org/10.1162/jocn.2010.21488

Wainio-theberge, S., Wolff, A., & Northoff, G. (2020). Bridging the gap – Spontaneous fluctuations shape stimulus-evoked spectral power. *bioRxiv*.

Wang, H., Poerio, G., Murphy, C., Bzdok, D., Jefferies, E., & Smallwood, J. (2017). *Dimensions of*

Experience: Exploring the Heterogeneity of the Wandering Mind. *c*. https://doi.org/10.1177/0956797617728727

Wang, H. T., Poerio, G., Murphy, C., Bzdok, D., Jefferies, E., & Smallwood, J. (2018). Dimensions of Experience: Exploring the Heterogeneity of the Wandering Mind. *Psychological Science*, *29*(1), 56–71. https://doi.org/10.1177/0956797617728727

Watanabe, M. (2017). The prefrontal cortex as an executive, emotional, and social brain. *The Prefrontal Cortex as an Executive, Emotional, and Social Brain*, 1–276. https://doi.org/10.1007/978-4-431-56508-6

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and Validation of Brief Measures of Positive and Negative Affect: The PANAS Scales. *Journal of Personality and Social Psychology*, *54*(6), 1063–1070.

Winkler, I., Brandl, S., Horn, F., Waldburger, E., Allefeld, C., & Tangermann, M. (2014). Robust artifactual independent component classification for BCI practitioners. *Journal of Neural Engineering*, *11*(3), 035013. https://doi.org/10.1088/1741-2560/11/3/035013

Winkler, I., Haufe, S., & Tangermann, M. (2011). Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals. *Behavioral and Brain Functions*, *7*(1), 30. https://doi.org/10.1186/1744-9081-7-30

Wittgenstein, L. (2009). *Philosophical investigations*. John Wiley & Sons.

Wolff, A., Berberian, N., Golesorkhi, M., Gomez-pilar, J., & Zilio, F. (2022). Intrinsic neural timescales: Temporal integration and segregation. *Trends in Cognitive Sciences*, *January*. https://doi.org/10.1016/j.tics.2021.11.007

Wolff, A., de la Salle, S., Sorgini, A., Lynn, E., Blier, P., Knott, V., & Northoff, G. (2019). Atypical Temporal Dynamics of Resting State Shapes Stimulus-Evoked Activity in Depression—An EEG Study on Rest–Stimulus Interaction. *Frontiers in Psychiatry*, *10*(October), 1–16. https://doi.org/10.3389/fpsyt.2019.00719

Wolff, A., Gomez-Pilar, J., Nakao, T., & Northoff, G. (2019). Interindividual neural differences in moral decision-making are mediated by alpha power and delta/theta phase coherence. *Scientific Reports*, *9*(1), 1–13. https://doi.org/10.1038/s41598-019-40743-y

Wolff, A., Yao, L., Gomez-Pilar, J., Shoaran, M., Jiang, N., & Northoff, G. (2019). Neural variability quenching during decision-making: Neural individuality and its prestimulus complexity. *NeuroImage*, *192*(February), 1–14. https://doi.org/10.1016/j.neuroimage.2019.02.070

Wolinski, N., Cooper, N. R., Sauseng, P., & Romei, V. (2018). The speed of parietal theta frequency drives visuospatial working memory capacity. *PLoS Biology*, *16*(3), 1–17. https://doi.org/10.1371/journal.pbio.2005348

Wolman, A., Çatal, Y., Wolff, A., Wainio-Theberge, S., Scalabrini, A., Ahmadi, A. E., & Northoff, G. (2023). Intrinsic neural timescales mediate the cognitive bias of self – temporal integration as key mechanism. *NeuroImage*, *268*, 119896. https://doi.org/10.1016/j.neuroimage.2023.119896

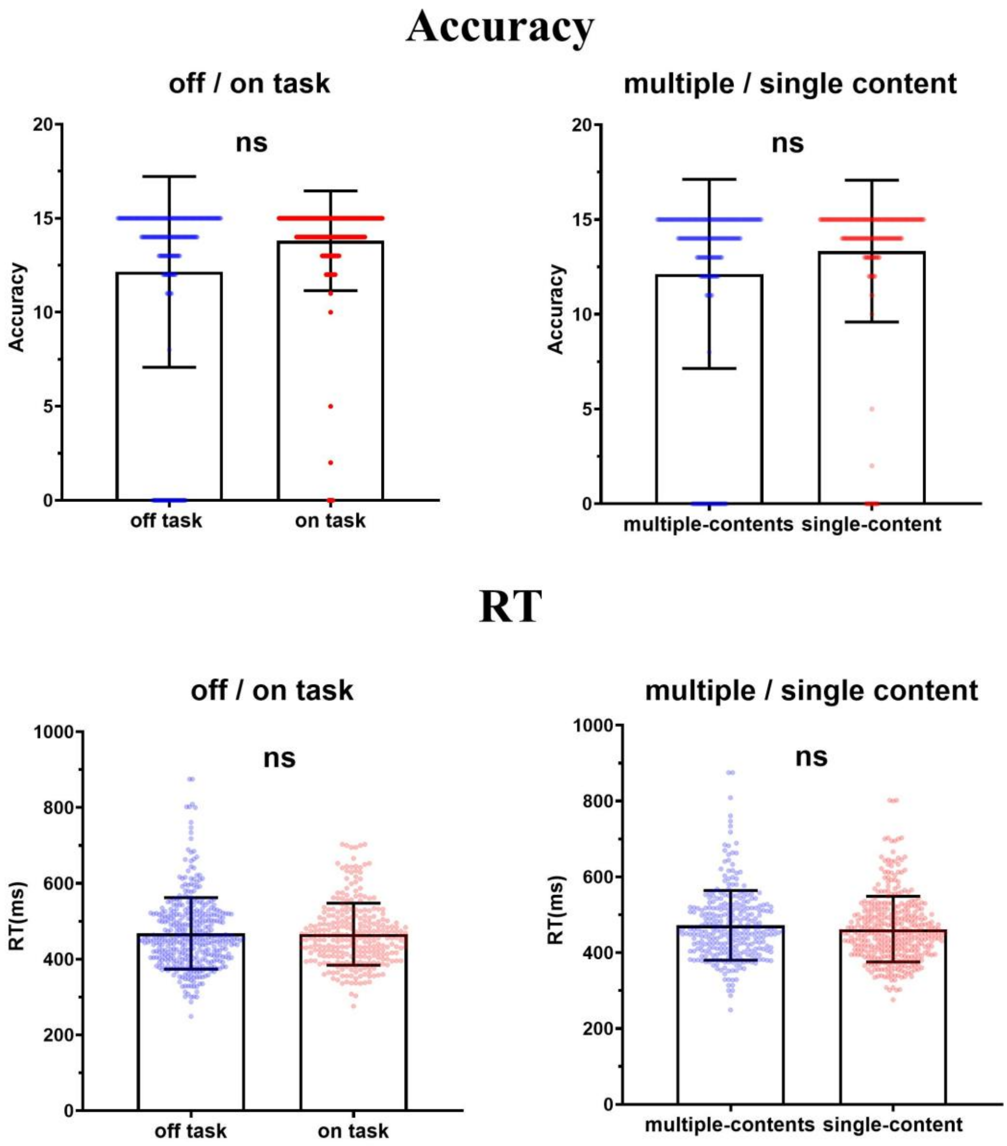
Wood, S. N. (2017). *Generalized Additive Models: An Introduction with R* (2nd ed.). Chapman and Hall/CRC.

Xu, P., Huang, Y., & Luo, Y. (2010). Establishment and assessment of native Chinese affective video system. *Chin. Ment. Health J*, *24*, 551–554.

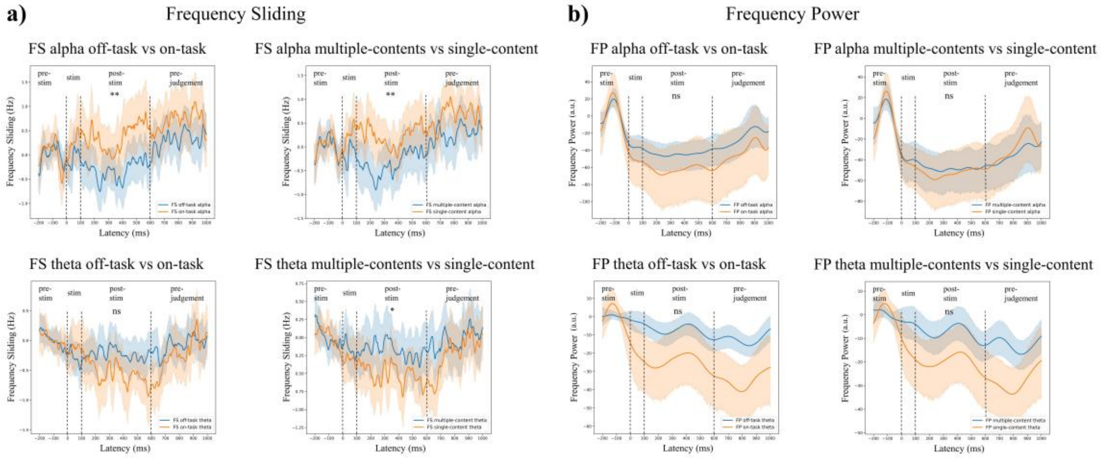
Supplementary materials

Study 1

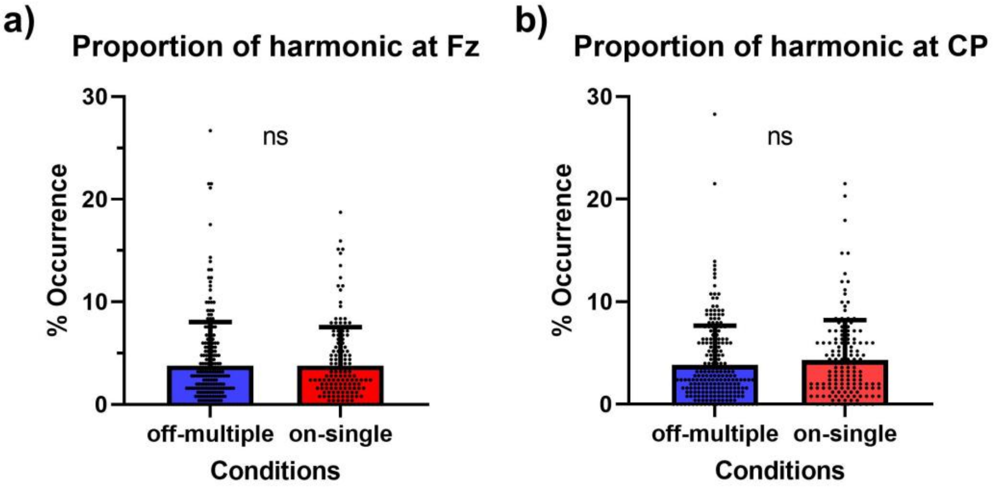
Supplementary figures



Supplementary Figure 1. Results of accuracy and RT between off task and on task, multiple contents and single content. The differences between conditions were tested by LMM for RT and GLMM for accuracy. There're no significant differences on RT and accuracy. Error bars mean SD; ns: no significance

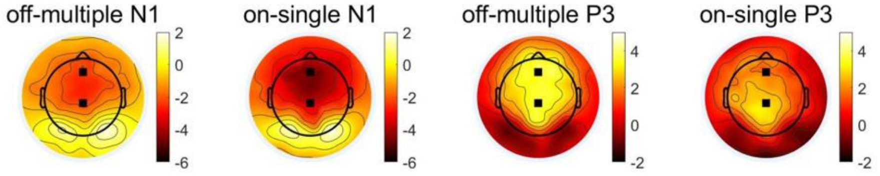


Supplementary Figure 2. FS and FP during different thought types (off task, on task, multiple contents, single content). a): FS during different thought types. There are significant differences between off- / on- thought and multiple- / single- content during post-stim relative values on both alpha and theta bands. **b): FP during different thought types.** Significance were not found on both frequency bands. **: p<0.01; *: p<0.05; ns: no significance

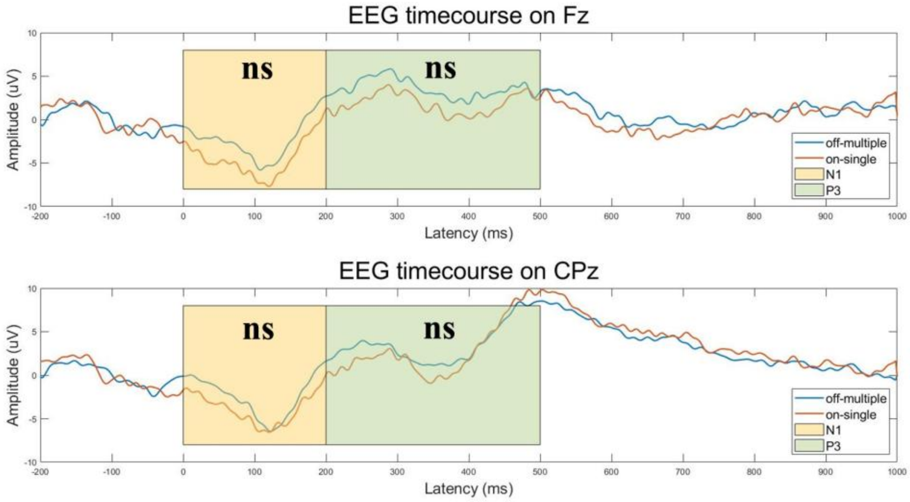


Supplementary Figure 3. T-test between off-multiple and on-single frequency harmonic on Fz and CPz. There are no significant differences between the proportion of harmonic of off-multiple and on-single on both a) Fz and b) CPz. Error bar mean SD; ns: no significance

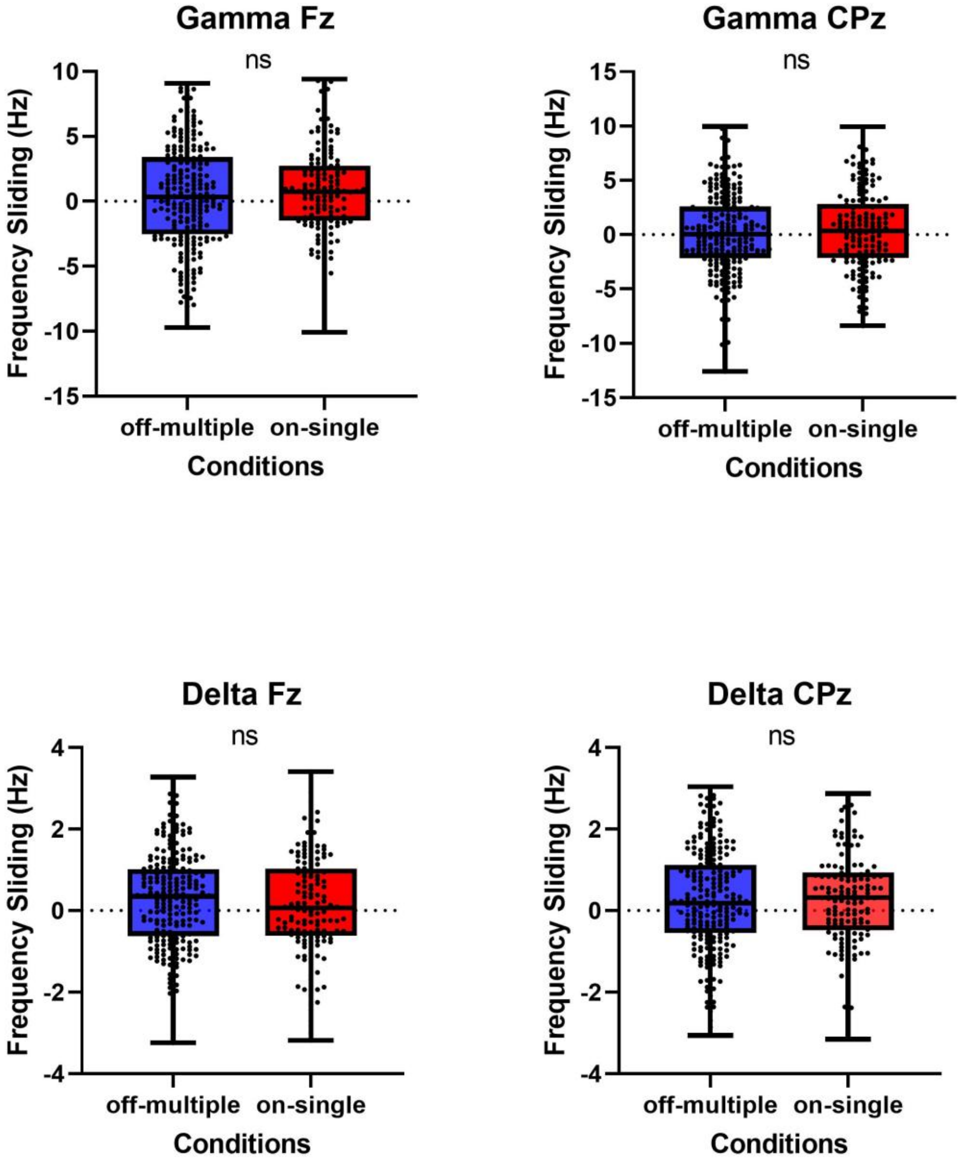
a) ERPs topography



b) EEG timecourse



Supplementary Figure 4. ERP results a). Topography of ERP components. b). The EEG timecourses on electrodes Fz and CPz. The LMM test on N1 (the component from 0 ms to 200 ms) and P3 (the component from 200 ms to 500 ms) between off-multiple and on-single on both Fz and CPz were applied. No significant difference was found on both components. ns: no significance



Supplementary Figure 5. delta and gamma FS results. FS on delta (3 Hz – 4 Hz) and gamma (30 Hz – 40 Hz) were analyzed on both Fz and CPz electrodes. The results show no significant differences on delta and gamma. ns: no significance

Stimuli Information

Standard stimuli：

A, B, D, E, F, G, H, I, J, M, N, Q, R, T, Y

Deviant Stimuli (Targets)：

a, b, d, e, f, g, h, i, j, k, n, q, r, t, y

Novel Stimuli：

Training session：З，ф，д，я，ч

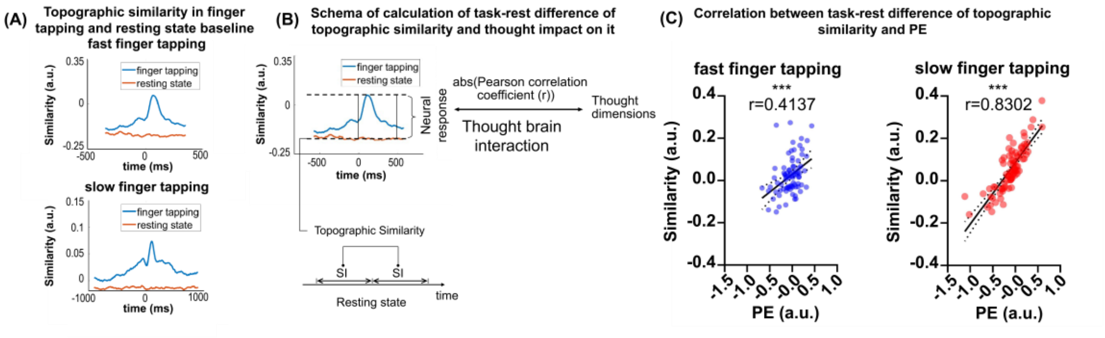
Block 1 和 Block 4：Bhutanese：ང，ཀ，ཁ，ག，ན；Georgian：ჳ，ღ，ი，ტ，რ；Khmer：ឆ，◌ឹ，េ◌，◌ុ，◌ា。

Block 2 和 Block 5: Bhutanese：◌ུ，◌ེ，◌ོ，ཏ，ཟ；Georgian：ფ，გ，ჯ，კ，ლ；Khmer：ស，ដ，ថ，ហ，ញ。

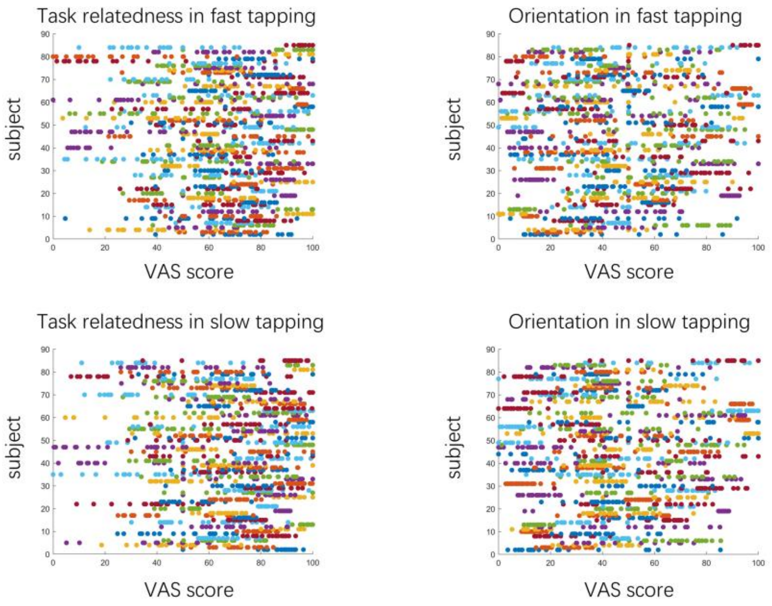
Block 3 和 Block6：Bhutanese：◌ི，ཙ，ཤ，འ，ཡ；Georgian：ზ，ც，ძ，ქ，წ；Khmer：ឋ，ខ，វ，ប，ន。

Study 2

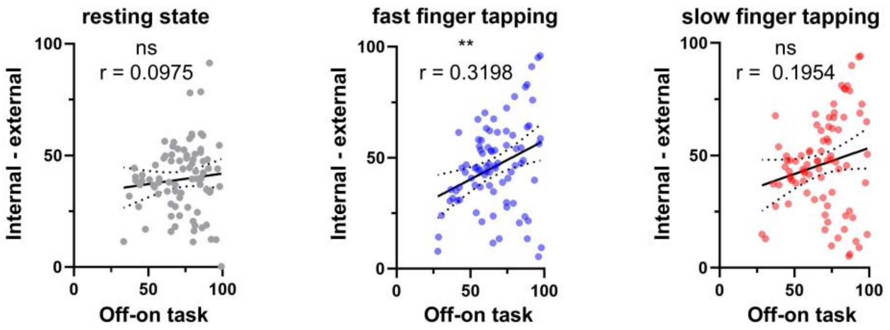
Supplementary figures



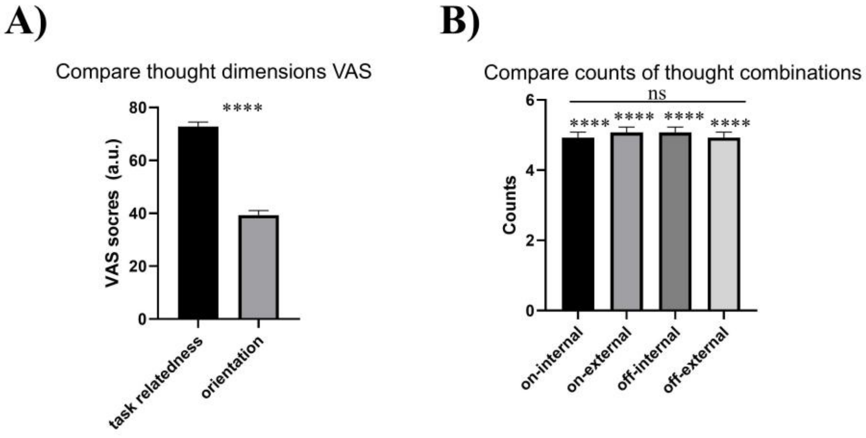
Supplementary figure 1. The calculation of task-rest difference of topographic similarity and its relationship with PE. A) Topographic similarity during finger tapping and resting state baseline. Here we show that the resting state baseline is stable across time, whereas topographic similarity peaks during the post-stimulus period in both fast and slow finger tapping. **B) Schema of calculation of task-rest difference of topographic similarity.** The topographic similarity in the resting state was calculated as the baseline for each participant. The calculation process is similar to that used for the finger tapping condition, with only one difference: the resting-state signal was epoched at SIs, with 0.8s epochs for the fast condition and 1.9s epochs for the slow condition. For each epoch, we calculated its topographic similarity with the corresponding time points of the previous epoch. Finally, all the epoch values at each timepoint were averaged to obtain the resting state's topographic similarity for each participant, e.g. their baseline. Then we calculated the correlation between the task-rest difference of topographic similarity and thought dimensions (task-relatedness and thought orientation) respectively in which we still take the same single trial results (as binned; see methods) of the thought probes as in their correlation with the precision index (see above). We used the absolute value of the correlation coefficient of the correlations as the measure of the thoughts' impact on topographic similarity **C) Correlation between task-rest difference of topographic similarity and PE.** Calculating task-rest difference of topographic similarity, we explored whether topographic similarity remained associated with PE. The results showed that even after subtracting the resting state baseline, the neural responses were still significantly correlated with PE in both fast and slow finger tapping tasks.



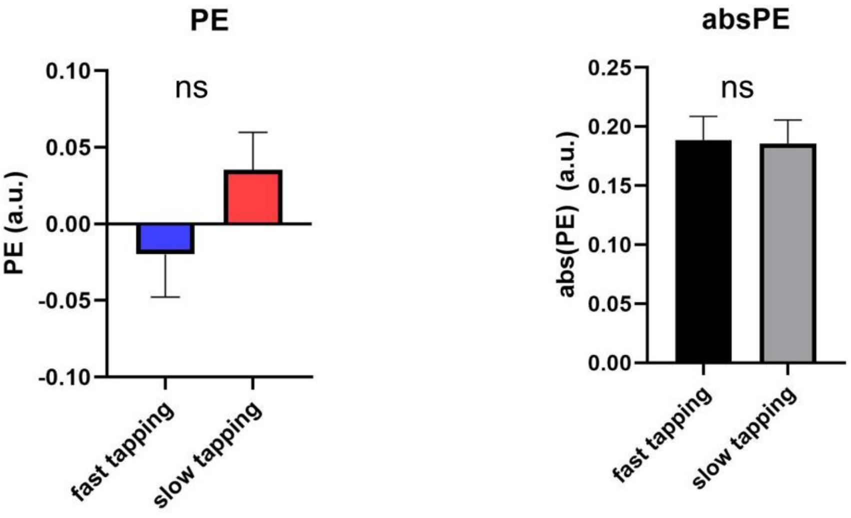
Supplementary figure 2. The VAS scores of all participants. The distributions of the thought VAS scores did not exhibit a bimodal pattern but rather a continuum within and across participants.



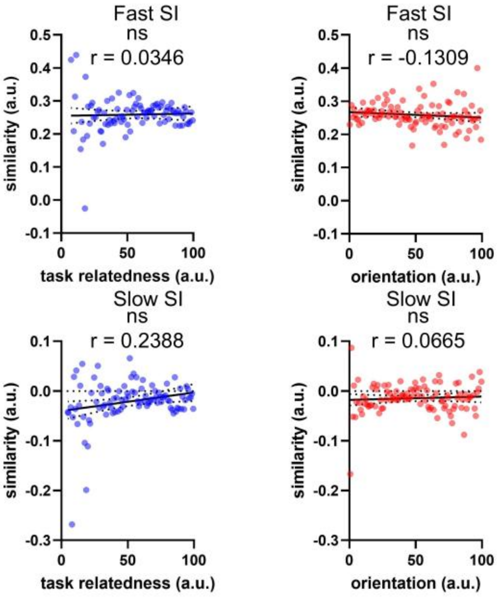
Supplementary Figure 3. Correlation between task-relatedness and thought orientation scores across conditions. Scatter plots showing the relationship between task-relatedness and thought orientation scores in the three experimental conditions: (A) resting state, (B) fast finger tapping, and (C) slow finger tapping. The plots highlight a noticeable association between the two dimensions during the fast finger tapping condition, while no apparent relationship is observed in the resting state or slow finger tapping condition. These results indicate condition-specific differences in the interplay between task-relatedness and thought orientation. Note: ns: none significance; **: p<0.01.



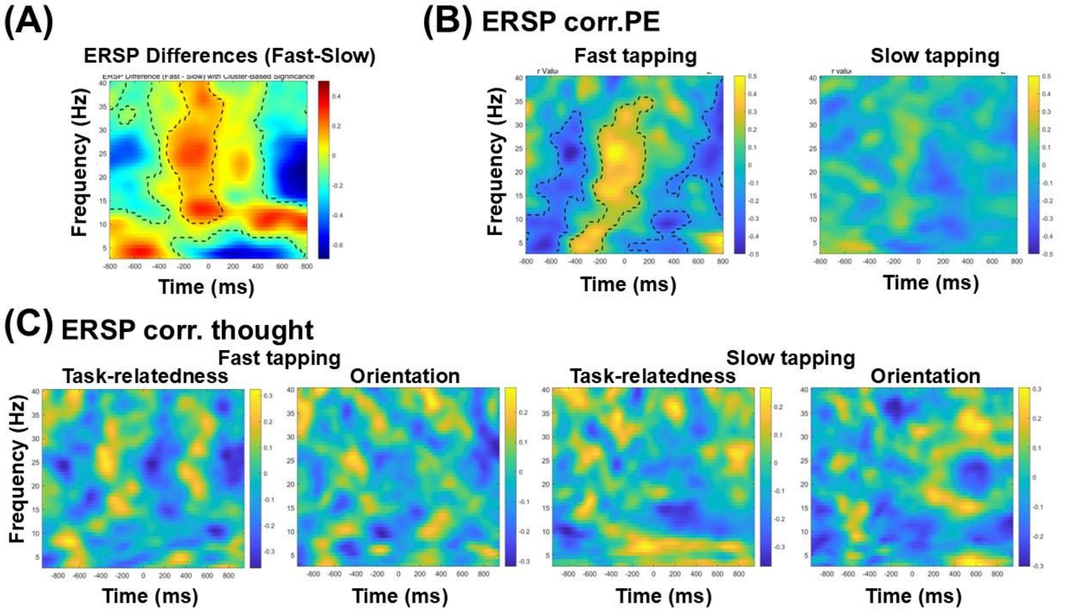
Supplementary Figure 4. Comparison of thought dimension ratings across conditions. (A) Bar plots depicting participants' VAS ratings for task-relatedness (off-task vs. on-task) and thought orientation (internal vs. external) in resting state. The plots reveal that task-relatedness ratings are consistently higher than thought orientation ratings in resting state. **(B) Bar plots illustrating the mean trial counts for the four thought categories (on-task/internal, off-task/internal, on-task/external, and off-task/external) in resting state.** The distribution shows no significant differences during the resting state, but the counts for all combinations are significantly higher than 0. Note: ****: p<0.0001; ns: none significance.



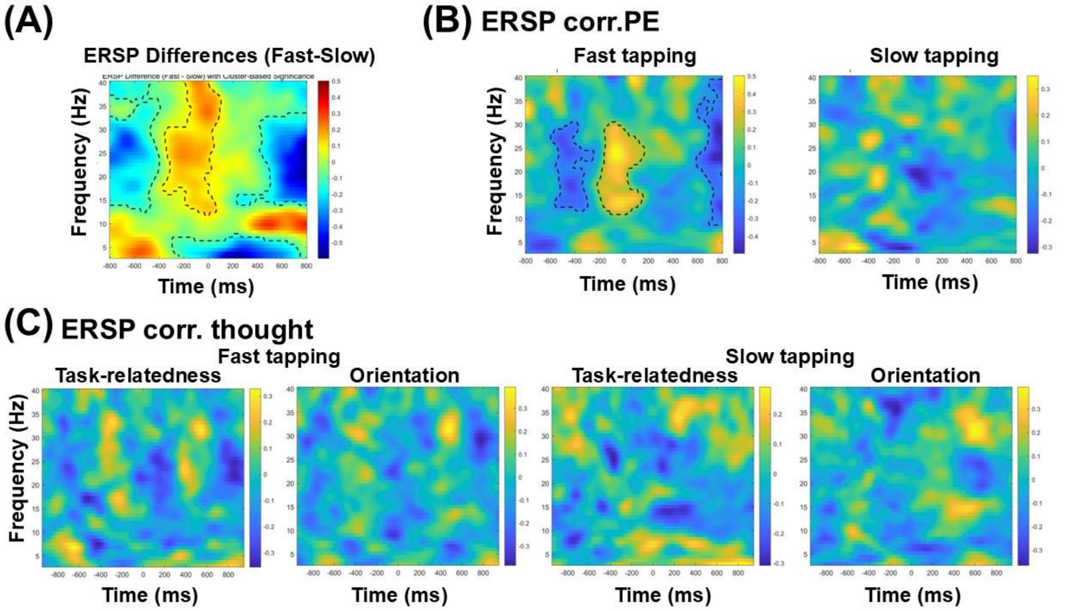
Supplementary Figure 5. Comparison of PE across fast and slow finger tapping conditions. Left figure: Comparison of PE between fast and slow finger tapping tasks. No significant difference were found of PE between fast and slow finger tapping. **Right figure: comparison of the absolute value of PE between fast and slow finger tapping conditions.** The result also showing no significant difference. These findings suggest that the duration of tapping intervals (shorter in fast tapping and longer in slow tapping) does not systematically affect PE. Note: ns: none significance.



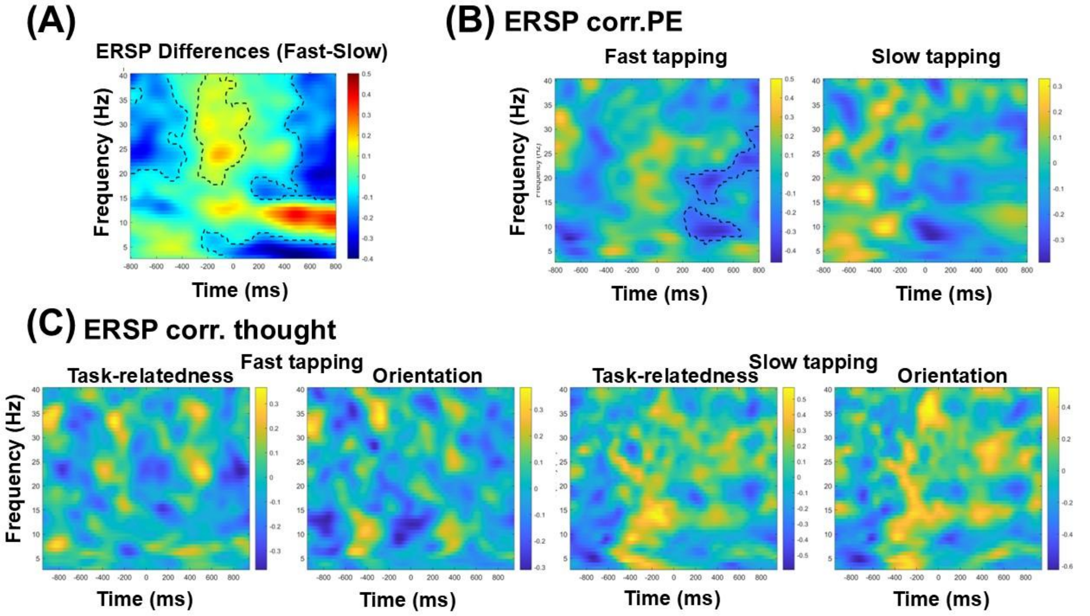
Supplementary Figure 6. Correlation between resting-state topographic similarity and thought dimensions across conditions. Scatter plots illustrating the relationship between resting-state topographic similarity and the two thought dimensions—task-relatedness and thought orientation. No significant correlations were observed for either thought dimension in both conditions (fast SI = 0.8s or slow SI = 1.9s), suggesting that resting-state topographic similarity is not associated with task-relatedness or thought orientation in resting state. Note: ns: none significance.



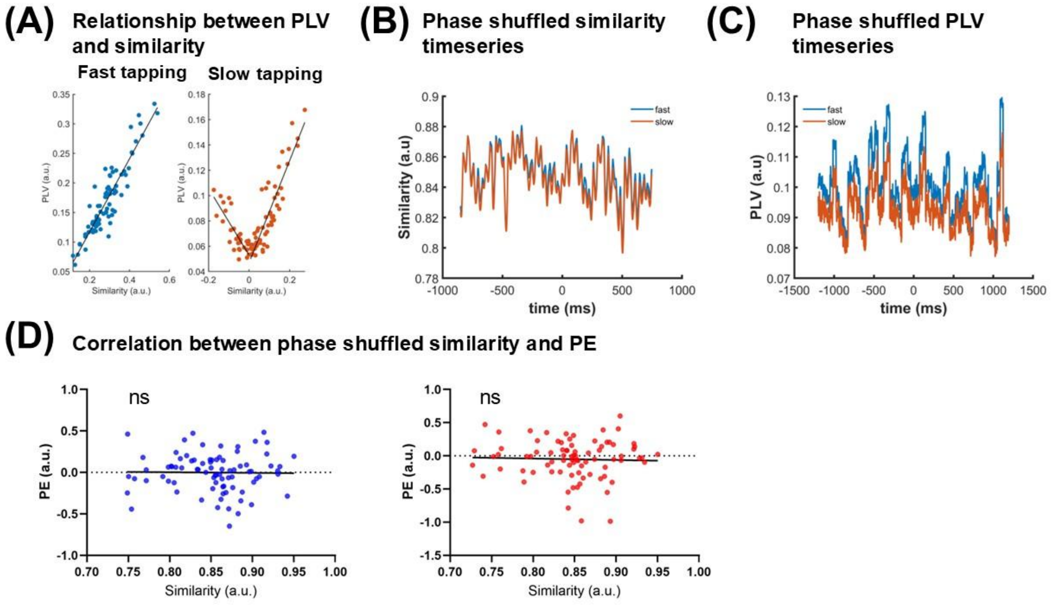
Supplementary figure 7. Time–frequency analysis of ERSP differences and correlations with behavior and thought at Fz. (A) Condition differences in ERSP between fast and slow tapping. Warm colors indicate greater power during fast tapping; cool colors indicate greater power during slow tapping. (B) Correlations between ERSP power and PE under fast (left) and slow (right) conditions. (C) Correlations between ERSP power and thought probe ratings (task-relatedness and orientation) under fast (left two panels) and slow (right two panels) tapping. In all panels, black dashed contours mark statistically significant clusters identified through cluster-based permutation testing ($p < 0.05$, corrected). Color scales in (A) reflect power differences (fast – slow), while in (B) and (C) they represent Pearson's correlation coefficients (r values).



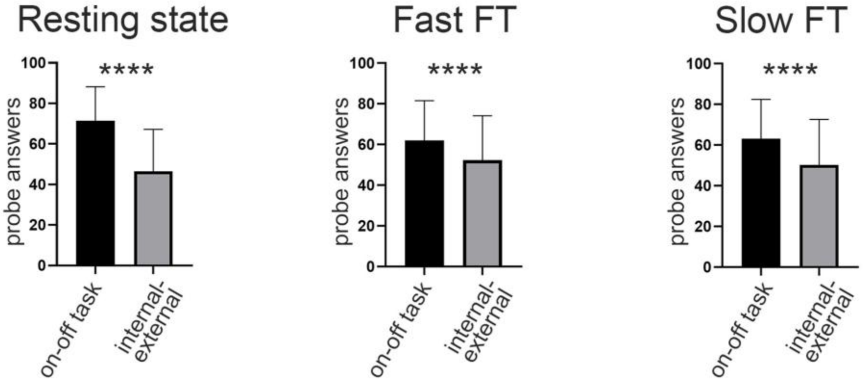
Supplementary figure 8. Time–frequency analysis of ERSP differences and correlations with behavior and thought at Cz. (A) Condition differences in ERSP between fast and slow tapping. Warm colors indicate greater power during fast tapping; cool colors indicate greater power during slow tapping. (B) Correlations between ERSP power and PE under fast (left) and slow (right) conditions. (C) Correlations between ERSP power and thought probe ratings (task-relatedness and orientation) under fast (left two panels) and slow (right two panels) tapping. In all panels, black dashed contours mark statistically significant clusters identified through cluster-based permutation testing ($p < 0.05$, corrected). Color scales in (A) reflect power differences (fast – slow), while in (B) and (C) they represent Pearson's correlation coefficients (r values).



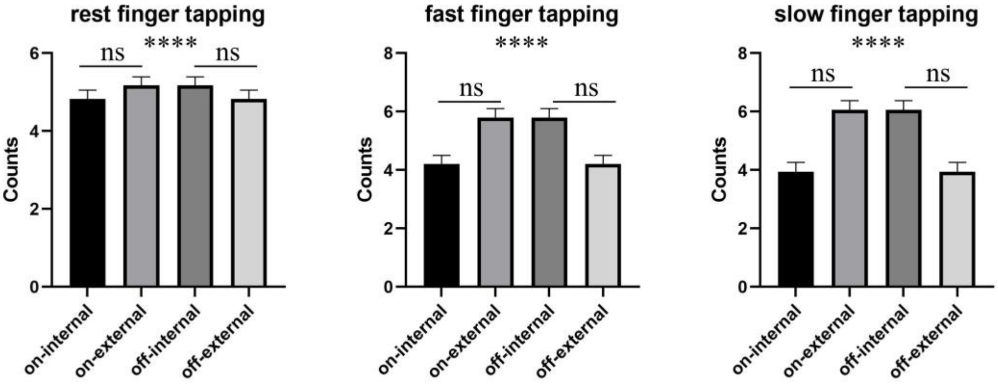
Supplementary figure 9. Time–frequency analysis of ERSP differences and correlations with behavior and thought at Pz. (A) Condition differences in ERSP between fast and slow tapping. Warm colors indicate greater power during fast tapping; cool colors indicate greater power during slow tapping. (B) Correlations between ERSP power and PE under fast (left) and slow (right) conditions. (C) Correlations between ERSP power and thought probe ratings (task-relatedness and orientation) under fast (left two panels) and slow (right two panels) tapping. In all panels, black dashed contours mark statistically significant clusters identified through cluster-based permutation testing ($p < 0.05$, corrected). Color scales in (A) reflect power differences (fast – slow), while in (B) and (C) they represent Pearson's correlation coefficients (r values).



Supplementary Figure 10. Phase based analysis of PLV and topographic similarity. (A) Raw scatterplot showing the piecewise association between PLV and untransformed topographic similarity under the slow tapping condition, due to the presence of negative similarity values. (B) Topographic similarity time course before and after phase-shuffling, showing elimination of the peak observed in the original data. (C) PLV time course before and after phase-shuffling. The characteristic 0–300 ms post-stimulus peak disappears after shuffling. (D) Correlations between topographic similarity and PE under both tapping conditions vanish after phase-shuffling. Note: *: $p<0.05$; **: $p<0.01$; ns: not significant.

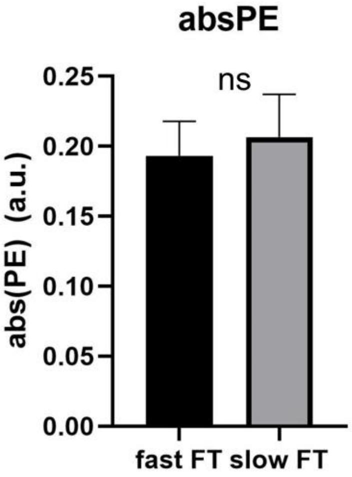


Supplementary Figure 11. Comparison of task-relatedness and thought orientation VAS scores in the replication dataset across conditions. Consistent with the findings from the first dataset, thought orientation scores were significantly lower than task-relatedness scores in all three conditions, demonstrating the replicability of the observed differences between the two thought dimensions. Note: ****: p<0.0001.

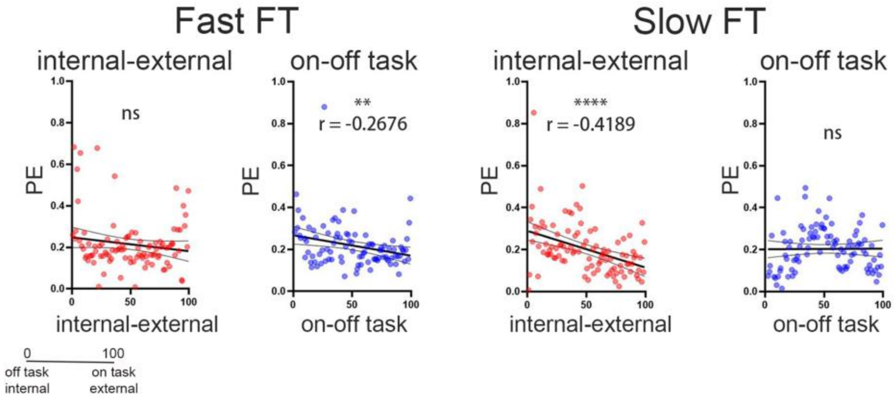


Supplementary Figure 12. Distribution of thought categories across conditions in the replication dataset. Statistical analysis results indicate no significant differences among the four thought categories during the resting state, as revealed by the Friedman test. However, significant differences were observed among the categories during fast and slow finger tapping conditions.

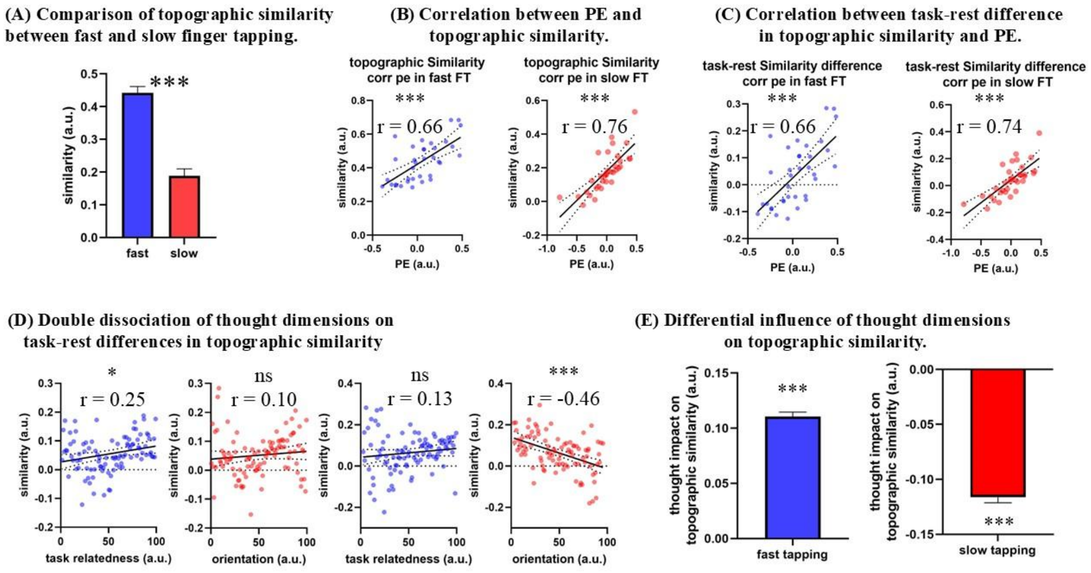
Despite these overall differences, multiple comparison tests showed no significant pairwise differences between any of the four categories in either fast or slow finger tapping. These findings, consistent with the first dataset, confirm that task-relatedness and thought orientation represent distinct cognitive dimensions without strict correspondence between specific thought combinations. Note: ns: none significance. ****: p<0.0001.



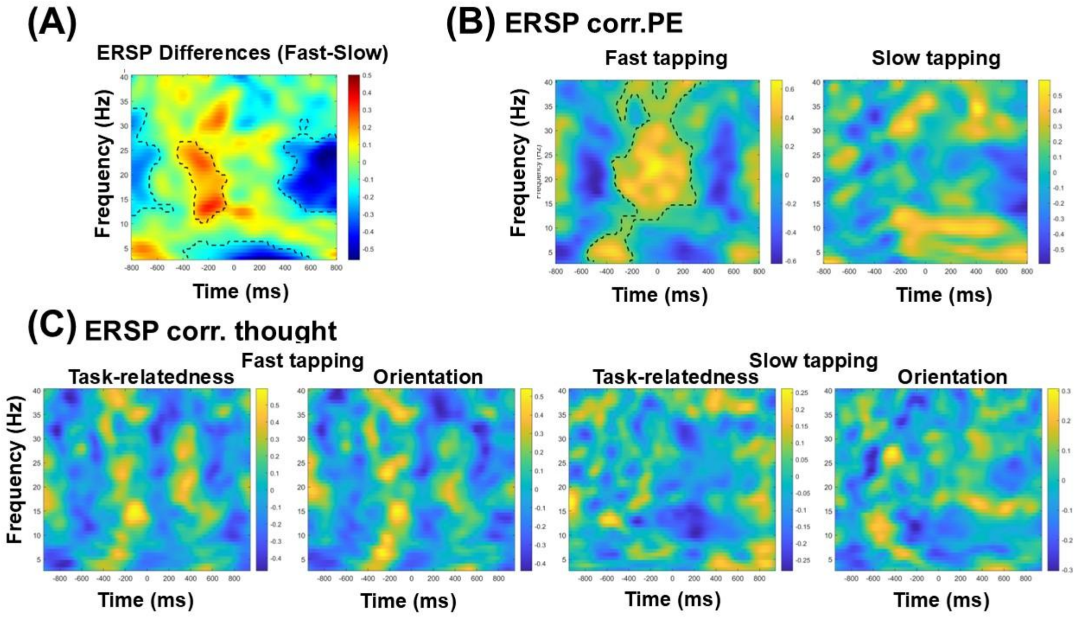
Supplementary figure 13. Comparison of the absolute value of PE between fast and slow tapping in the replication dataset. The absolute value PE was not significantly different between fast and slow FT. Note: ns: none significance.



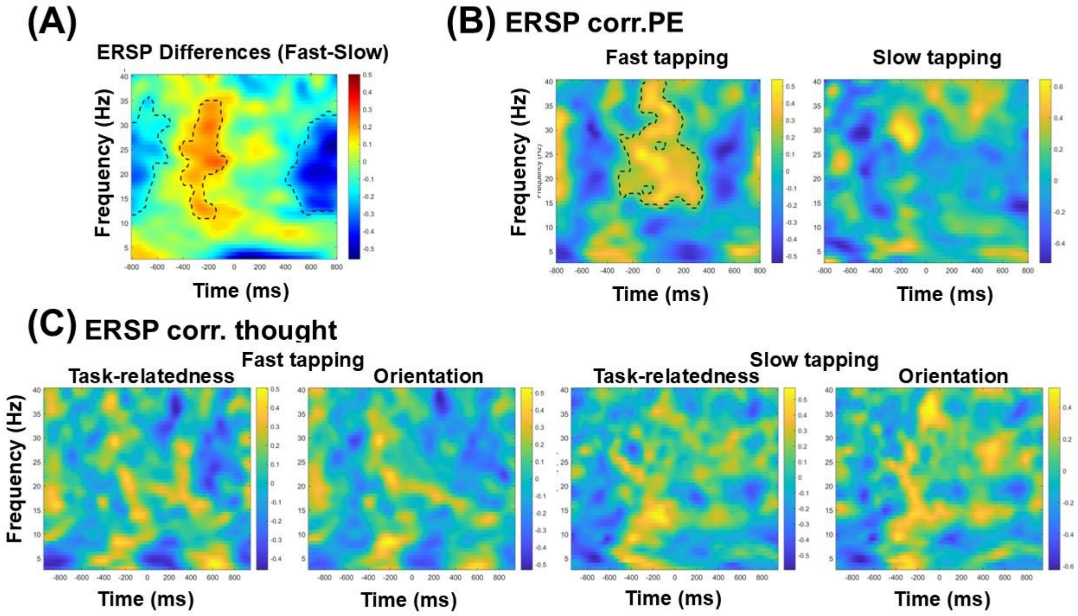
Supplementary Figure 14. Double dissociation of the correlation between PE and thought dimensions across tapping conditions in the replication dataset. In fast FT, PE is significantly correlated with task-relatedness but not with thought orientation, highlighting a selective association with task-relatedness at faster tapping speeds. In slow FT, PE is significantly correlated with thought orientation but not with task-relatedness, indicating a selective association with thought orientation at slower tapping speeds. These findings replicate the double dissociation observed in the first dataset, further supporting the distinction between task-relatedness and thought orientation as independent thought dimensions. Note: ns: none significance; **: p<0.01; ****: p<0.0001.



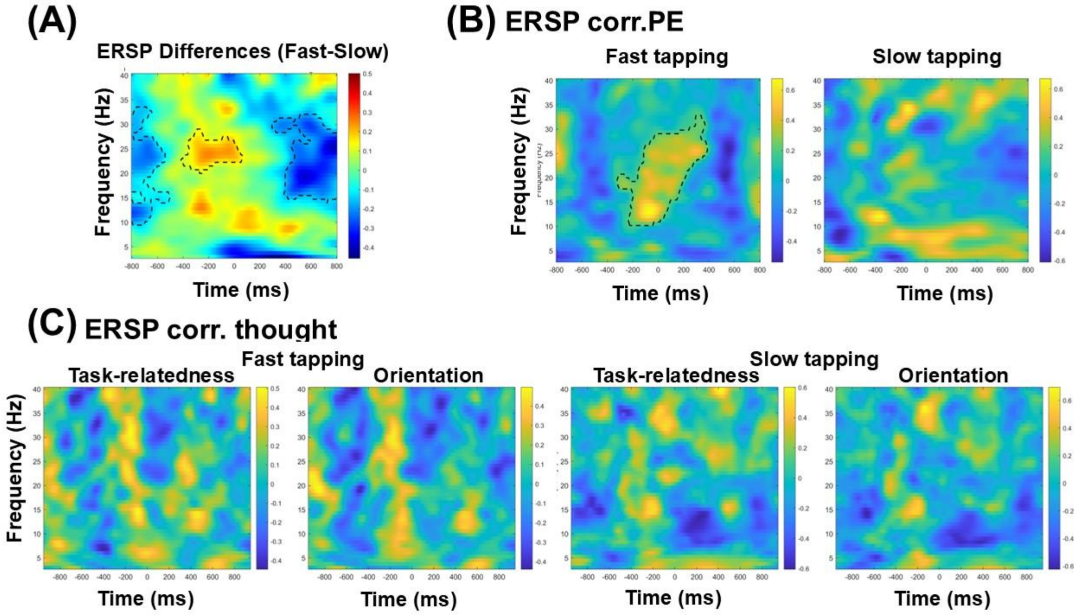
Supplementary Figure 15. Replication of the neural correlates of task-relatedness and thought orientation in the replication dataset. (A) Comparison of topographic similarity between fast and slow finger tapping. Topographic similarity is significantly higher during fast finger tapping (FT) compared to slow FT, replicating previous findings. **(B) Correlation between PE and topographic similarity.** Significant correlations are observed between PE and topographic similarity in both fast and slow FT conditions. **(C) Correlation between task-rest difference in topographic similarity and PE.** The task-rest difference in topographic similarity is significantly correlated with PE in both fast and slow FT conditions, highlighting the impact of PE on neural dynamics during task performance. **(D) Double dissociation of thought dimensions on task-rest differences in topographic similarity.** In fast FT, task-rest differences in topographic similarity are correlated with task-relatedness but not thought orientation. In slow FT, the opposite pattern is observed, with significant correlations only with thought orientation. **(E) Differential influence of thought dimensions on topographic similarity.** During fast FT, task-relatedness exerts a greater influence on topographic similarity, while during slow FT, thought orientation has a stronger effect. These findings replicate and extend the neural-level double dissociation between task-relatedness and thought orientation, further supporting their distinct contributions under different temporal contexts. Note: ns: none significance; ***: p<0.001.



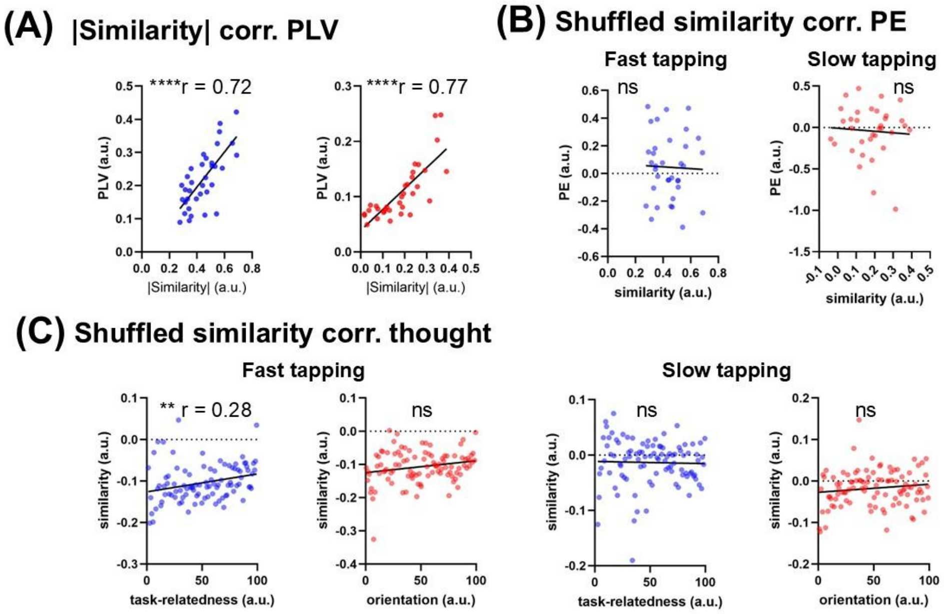
Supplementary figure 16. Time–frequency analysis of ERSP differences and correlations with behavior and thought at Fz on replication dataset. (A) Condition differences in ERSP between fast and slow tapping. Warm colors indicate greater power during fast tapping; cool colors indicate greater power during slow tapping. (B) Correlations between ERSP power and PE under fast (left) and slow (right) conditions. (C) Correlations between ERSP power and thought probe ratings (task-relatedness and orientation) under fast (left two panels) and slow (right two panels) tapping. In all panels, black dashed contours mark statistically significant clusters identified through cluster-based permutation testing ($p < 0.05$, corrected). Color scales in (A) reflect power differences (fast – slow), while in (B) and (C) they represent Pearson's correlation coefficients (r values).



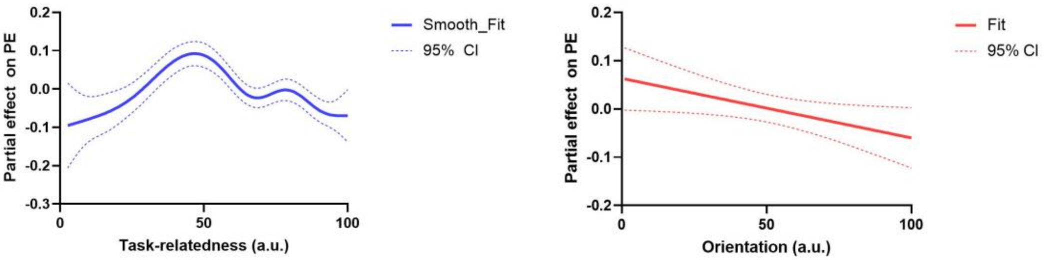
Supplementary figure 17. Time–frequency analysis of ERSP differences and correlations with behavior and thought at Cz on replication dataset. (A) Condition differences in ERSP between fast and slow tapping. Warm colors indicate greater power during fast tapping; cool colors indicate greater power during slow tapping. (B) Correlations between ERSP power and PE under fast (left) and slow (right) conditions. (C) Correlations between ERSP power and thought probe ratings (task-relatedness and orientation) under fast (left two panels) and slow (right two panels) tapping. In all panels, black dashed contours mark statistically significant clusters identified through cluster-based permutation testing ($p < 0.05$, corrected). Color scales in (A) reflect power differences (fast – slow), while in (B) and (C) they represent Pearson's correlation coefficients (r values).



Supplementary figure 18. Time–frequency analysis of ERSP differences and correlations with behavior and thought at Pz on replication dataset. (A) Condition differences in ERSP between fast and slow tapping. Warm colors indicate greater power during fast tapping; cool colors indicate greater power during slow tapping. (B) Correlations between ERSP power and PE under fast (left) and slow (right) conditions. (C) Correlations between ERSP power and thought probe ratings (task-relatedness and orientation) under fast (left two panels) and slow (right two panels) tapping. In all panels, black dashed contours mark statistically significant clusters identified through cluster-based permutation testing ($p < 0.05$, corrected). Color scales in (A) reflect power differences (fast – slow), while in (B) and (C) they represent Pearson's correlation coefficients (r values).



Supplementary Figure 19. Phase-based validation of topographic similarity using correlation and phase-shuffling analyses. (A) Scatterplots showing strong positive correlations between PLV and the absolute value of topographic similarity under both tapping conditions. (B) After phase-shuffling, the correlation between topographic similarity and PE is abolished under both conditions. (C) Correlation plots between phase-shuffled topographic similarity and thought dimensions. A significant correlation with task-relatedness was observed only under fast tapping, while all other associations were non-significant.



Supplementary Figure 20. An example of GAM fits illustrating the nonlinear relationship between task-relatedness and PE and linear relationship between orientation and PE.

Supplementary tables

Supplementary Table 1. Fast tapping Friedman test multiple comparison results

Comparison	**Rank sum diff.**	**Adjusted P Value**
on-internal vs. on-external	-34	0.253
on-internal vs. off-internal	-34	0.253
on-internal vs. off-external	0	>0.9999
on-external vs. off-internal	0	>0.9999
on-external vs. off-external	34	0.253
off-internal vs. off-external	34	0.253

Supplementary Table 2. Slow tapping Friedman test multiple comparison results

Comparison	Rank sum diff.	Adjusted P Value
on-internal vs. on-external	-38	0.1389
on-internal vs. off-internal	-38	0.1389
on-internal vs. off-external	0	>0.9999
on-external vs. off-internal	0	>0.9999
on-external vs. off-external	38	0.1389
off-internal vs. off-external	38	0.1389

Supplementary table 3. Details of LMMs and GAMs

Fast Tapping

LMM raw values

Predictor	Beta	SE	t	CI_lower	CI_upper

Task relatedness	-0.0006	0.0003	-1.8659	-0.0011	0.0000
Orientation	0.0000	0.0003	0.0432	-0.0005	0.0005

GAM

Predictor	edf	F_value	p_value
Task relatedness	2.2302	2.2635	0.1013
Orientation	1.0003	13.8395	0.0002

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	0.0001	0.0003	0.2532	-0.0005	0.0007
Orientation	0.0010	0.0003	3.8337	0.0005	0.0015

Slow Tapping

LMM raw values

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0010	0.0003	-2.8537	-0.0017	-0.0003

Orientation	-0.0002	0.0003	-0.8047	-0.0009	0.0004

GAM

Predictor	edf	F_value	p_value
Task relatedness	5.0273	3.8886	0.0009
Orientation	1.0369	16.9425	0.0000

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	0.0000	0.0003	-0.0212	-0.0007	0.0007
Orientation	0.0010	0.0003	3.3622	0.0004	0.0016

Supplementary table 4. Bayesian Mediation Analysis of Task-Relatedness and Orientation Effects on PE

Condition	**Thought dimension**	**Variable**	**Mean**	**q5**	**q95**	$\hat{r}$
Fast	Task-relatedness	Indirect	-0.11	*-0.2*	*-0.04*	1.00

		Direct	0.04	-0.07	0.15	1.00
		Total	-0.07	*-0.15*	*0*	1.00
	Orientation	Indirect	-0.59	-1.84	0.56	2.82
		Direct	0.41	-0.74	1.67	2.81
		Total	-0.18	*-0.25*	*-0.1*	1.03
Slow	Task-relatedness	Indirect	-0.12	*-0.16*	*-0.08*	1.00
		Direct	0.02	-0.06	0.11	1.00
		Total	-0.1	*-0.17*	*-0.02*	1.00
	Orientation	Indirect	-0.35	-0.81	0.13	1.02
		Direct	0.35	-0.14	0.8	1.02
		Total	-0.009	*-0.012*	*-0.005*	1.00

Note: Effects whose 90% credible intervals do not include zero are interpreted as statistically meaningful (*italicized* in parentheses).

Supplementary table 5. r values of Pearson Correlations Among Orientation, Smooth Term s(orientation), and PE

	orientation	s(orientation)	PE
orientation	1.00	-1.00	-0.17
s(orientation)	-1.00	1.00	0.17
PE	-0.17	0.17	1.00

Supplementary table 6. Interaction GAM Analysis Comparing Nonlinear Contributions of Thought Dimensions on PE Across Conditions

Predictor	**F**	**p**
Task-Relatedness (T)	2.45	0.027
Orientation (O)	0.64	0.493

Supplementary table 7. Nonlinear modeling of the relationship between thought dimensions and topographic similarity across tapping conditions.

Fast Tapping

LMM raw values

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	0.0004	0.0002	2.5689	0.0001	0.0008
Orientation	0.0003	0.0001	1.9406	0.0000	0.0005

GAM

Predictor	edf	F_value	p_value
Task relatedness	3.7448	4.2763	0.0011
Orientation	1.0020	4.2675	0.0390

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	0.0000	0.0002	-0.2391	-0.0004	0.0003
Orientation	0.0000	0.0001	-0.0301	-0.0003	0.0003

Slow Tapping

LMM raw values

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	0.0001	0.0002	0.7033	-0.0002	0.0005
Orientation	-0.0002	0.0002	-1.0705	-0.0005	0.0001

GAM

Predictor	edf	F_value	p_value
Task relatedness	1.0004	1.9648	0.1612
Orientation	3.1511	1.0924	0.3683

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0001	0.0002	-0.5018	-0.0004	0.0003
Orientation	-0.0002	0.0002	-1.1412	-0.0005	0.0001

Supplementary table 8. Bayesian Mediation Estimates for the Associations Between Thought Dimensions and Topographic Similarity Across Tapping Conditions.

Condition	Thought dimension	Variable	Mean	q5	q95	**$\hat{r}$**
Fast	Task-relatedness	Indirect	0.14	*0.08*	*0.20*	1.00
		Direct	-0.04	-0.12	0.04	1.00
		Total	0.10	*0.05*	*0.15*	1.00
	Orientation	Indirect	45.50	-43.90	137.00	1.07
		Direct	-45.40	-137.00	43.90	1.07
		Total	0.06	*0.01*	*0.11*	1.00
Slow	Task-relatedness	Indirect	2.01	-6.15	17.40	1.84
		Direct	-1.97	-17.30	6.19	1.84
		Total	0.04	*-0.01*	*0.09*	1.00
	Orientation	Indirect	0.01	*0.01*	*0.02*	1.00
		Direct	-0.01	-0.05	0.04	1.00
		Total	0.01	-0.04	0.06	1.00

Note: Effects whose 90% credible intervals do not include zero are interpreted as statistically meaningful (*italicized* in parentheses).

Supplementary table 9. r values of correlations among task-relatedness, its smooth term, and topographic similarity under the slow tapping condition.

	Task-relatedness	s(task-relatedness)	Topographic similarity
Task-relatedness	1.00	1.00	0.04
s(task-relatedness)	1.00	1.00	0.04
Topographic similarity	0.04	1.00	1.00

Supplementary table 10. Nonlinear impact of the Relationship Between Thought Dimensions and PE Across timescales (tapping conditions) on replication dataset

Fast Tapping

LMM raw values

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0009	0.0002	-3.8930	-0.0013	-0.0004
Orientation	-0.0001	0.0002	-0.4151	-0.0005	0.0003

GAM

Predictor	edf	F_value	p_value
Task relatedness	2.2930	3.1067	0.0298
Orientation	3.7478	3.2626	0.0102

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0003	0.0002	-1.2020	-0.0007	0.0002
Orientation	-0.0003	0.0002	-1.3340	-0.0007	0.0001

Slow Tapping

LMM raw values

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0007	0.0002	-3.5314	-0.0011	-0.0003
Orientation	-0.0007	0.0002	-3.3478	-0.0011	-0.0003

GAM

Predictor	edf	F_value	p_value
Task relatedness	6.0999	7.0964	0.0000
Orientation	1.0003	17.7928	0.0000

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0001	0.0002	-0.5041	-0.0005	0.0003
Orientation	0.0005	0.0002	2.6413	0.0001	0.0009

Supplementary table 11. Bayesian Mediation Estimates for the Associations Between Thought Dimensions and PE on replication dataset.

Condition	**Thought dimension**	**Variable**	**Mean**	**q5**	**q95**	$\hat{r}$
Fast	Task-relatedness	Indirect	-0.13	*-0.21*	*-0.04*	1.00
		Direct	0.03	-0.07	0.15	1.00
		Total	-0.09	*-0.16*	*-0.02*	1.00

	Orientation	Indirect	0.03	*0.02*	*0.06*	1.00
		Direct	-0.01	-0.08	0.06	1.00
		Total	0.03	-0.04	0.1	1.00
Slow	Task-relatedness	Indirect	-0.11	*-0.15*	*-0.08*	1.00
		Direct	0.01	-0.06	0.09	1.00
		Total	-0.1	-0.18	-0.03	1.00
	Orientation	Indirect	-0.54	-1.29	0.11	2.68
		Direct	0.35	-0.30	1.11	2.67
		Total	-0.19	-0.27	-0.12	1.01

Note: Effects whose 90% credible intervals do not include zero are interpreted as statistically meaningful (*italicized* in parentheses).

Supplementary table 12. r values of Pearson Correlations Among Orientation, Smooth Term s(orientation), and PE on replication dataset

	orientation	s(orientation)	PE
orientation	1.00	-1.00	-0.19
s(orientation)	-1.00	1.00	0.19
PE	-0.19	0.19	1.00

Supplementary table 13. Interaction GAM Analysis Comparing Nonlinear Contributions of Thought Dimensions on PE Across Conditions on replication dataset

Predictor	F	p
Task-Relatedness (T)	9.66	<0.0001
Orientation (O)	160.62	<0.0001

Supplementary table 14. Nonlinear modeling of the relationship between thought dimensions and topographic similarity across tapping conditions on replication dataset.

Fast Tapping					
LMM raw values					
Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	0.0006	0.0003	2.4048	0.0001	0.0011
Orientation	0.0002	0.0003	0.7144	-0.0003	0.0007

GAM

Predictor	edf	F_value	p_value
Task relatedness	4.3084	6.3314	0.0000
Orientation	3.9575	5.7078	0.0001

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0002	0.0003	-0.8320	-0.0007	0.0003
Orientation	-0.0006	0.0003	-2.2302	-0.0011	-0.0001

Slow Tapping

LMM raw values

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	0.0000	0.0003	-0.1181	-0.0006	0.0006
Orientation	0.0004	0.0003	1.1779	-0.0002	0.0010

GAM

Predictor	edf	F_value	p_value
Task relatedness	2.7999	1.7507	0.1655
Orientation	4.1595	7.7648	0.0000

LMM nonlinearity controlled

Predictor	Beta	SE	t	CI_lower	CI_upper
Task relatedness	-0.0005	0.0003	-1.5519	-0.0011	0.0001
Orientation	-0.0007	0.0003	-2.1870	-0.0013	-0.0001

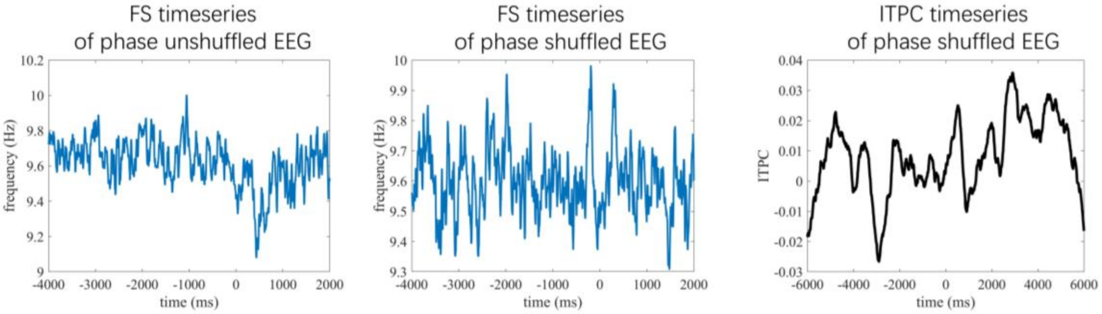
Supplementary table 15. Bayesian Mediation Estimates for the Associations Between Thought Dimensions and topographic similarity on replication dataset.

Condition	**Thought dimension**	**Variable**	**Mean**	**q5**	**q95**	**$\hat{r}$**
Fast	Task-relatedness	Indirect	0.19	*0.12*	*0.25*	1.00
		Direct	-0.03	-0.12	0.06	1.00
		Total	0.16	*0.09*	*0.23*	1.00

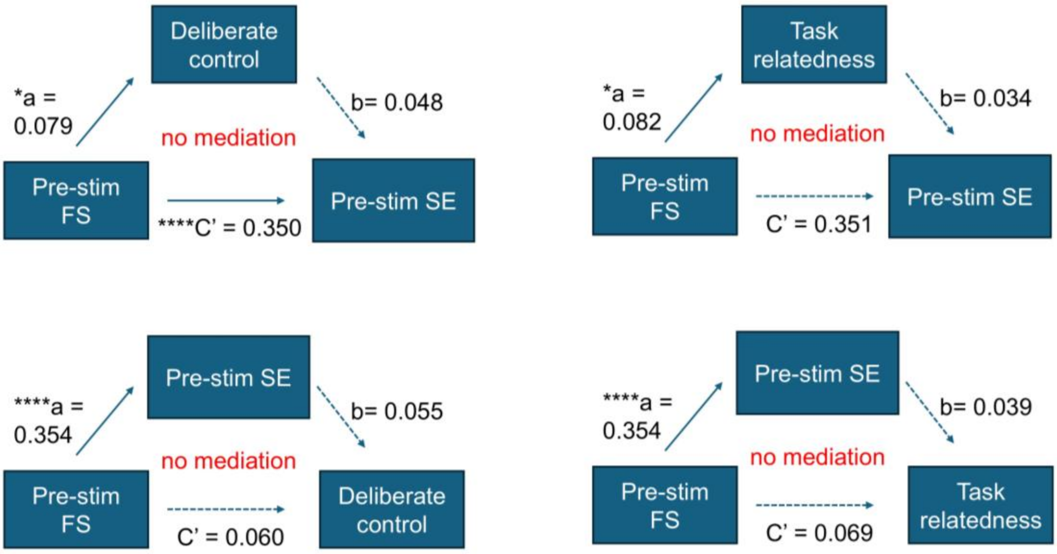
	Orientation	Indirect	0.18	*0.12*	*0.25*	1.00
		Direct	-0.03	-0.13	0.07	1.00
		Total	0.15	*0.08*	*0.22*	1.00
Slow	Task-relatedness	Indirect	0.14	*0.05*	*0.22*	1.00
		Direct	-0.07	-0.18	0.04	1.00
		Total	0.07	-0.01	0.14	1.00
	Orientation	Indirect	0.21	*0.14*	*0.28*	1.00
		Direct	-0.03	-0.13	0.07	1.00
		Total	0.18	*0.11*	*0.26*	1.00

Note: Effects whose 90% credible intervals do not include zero are interpreted as statistically meaningful (*italicized* in parentheses).

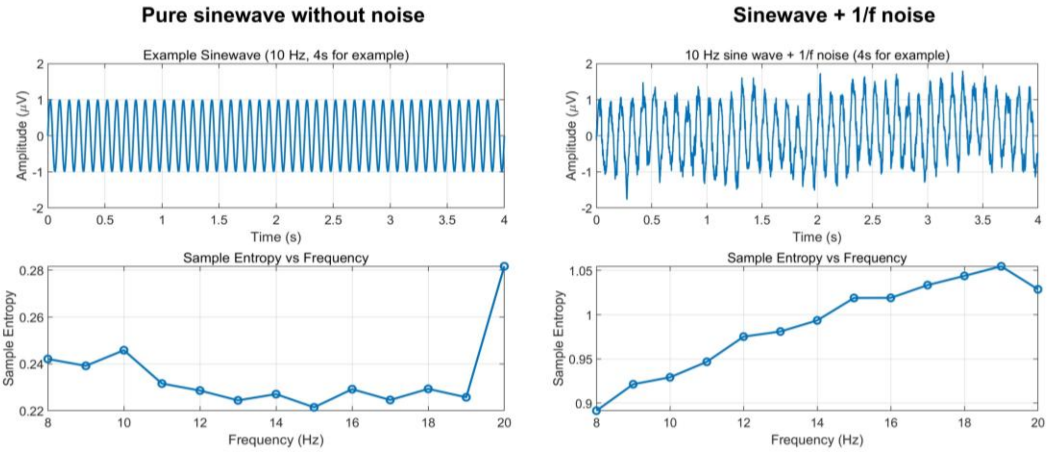
Study 3



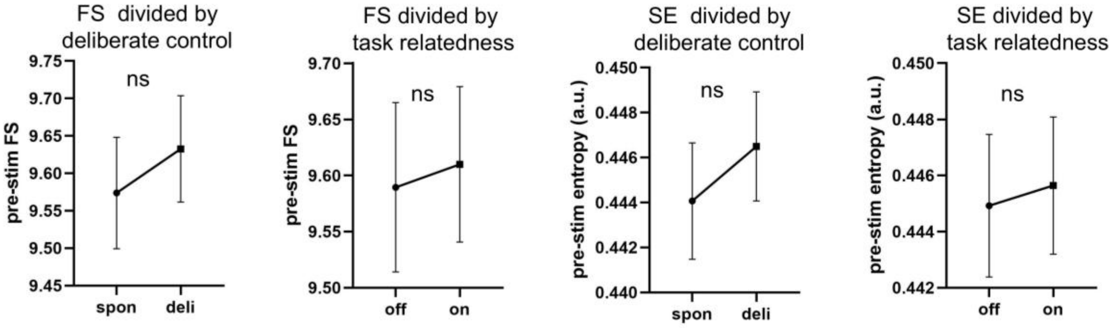
Supplementary Figure 1. Time series of unshuffled FS, phase-shuffled FS, and phase-shuffled ITPC, illustrating the impact of phase randomization on neural dynamics.



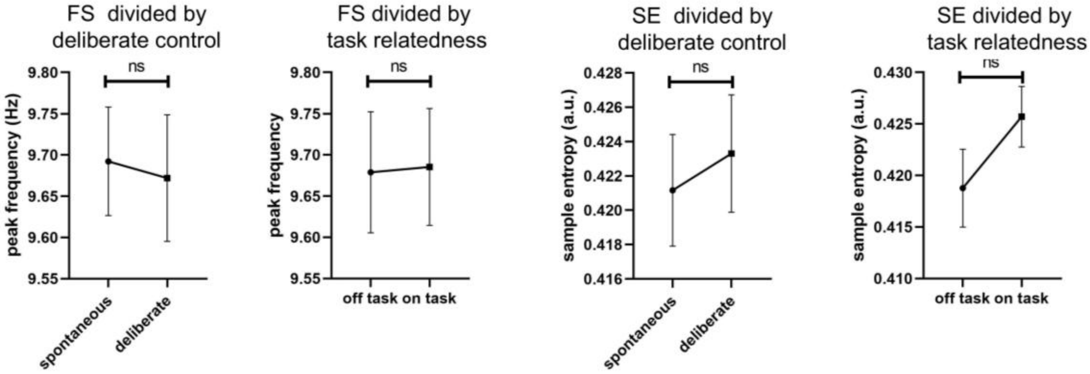
Supplementary Figure 2. Alternative Mediation Models Testing Thought Dimensions as Mediators or dependent Variables. Displayed are the results of mediation analyses in which the thought dimensions (deliberate control, task relatedness) were alternatively tested as mediators or dependent variables in the relationship between pre-stimulus FS and pre-stimulus SE. No mediation effects were observed under these alternative models. Note: *: p<0.05; ****: p<0.0001.



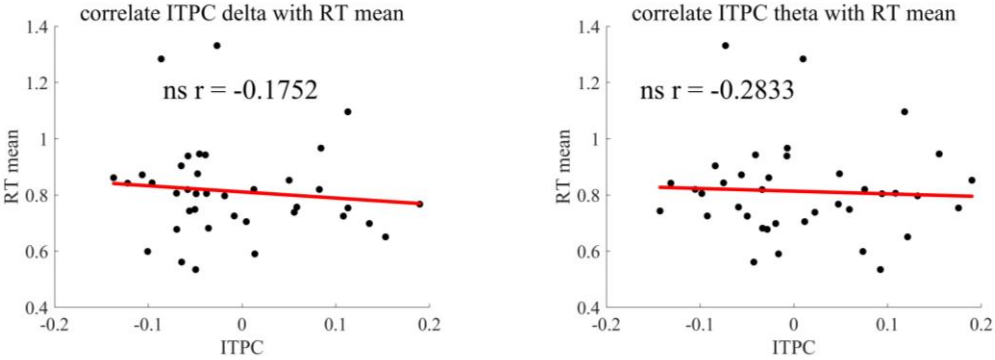
Supplementary Figure 3. Simulation demonstrating the relationship between FS and SE. (Left) Pure sinewave condition: Example 10 Hz sinewave (top) and the corresponding relationship between FS and SE (bottom). Increasing frequency did not produce a systematic change in sample entropy, indicating that entropy and oscillatory frequency were independent for purely rhythmic signals. (Right) Sinewave + 1/f noise condition: Example 10 Hz sinewave with added 1/f noise (top) and the resulting FS-SE relationship (bottom). When scale-free noise was introduced, sample entropy increased monotonically with frequency. This pattern shows that the coupling between frequency and entropy arises only in the presence of scale-free (1/f) background dynamics, mirroring the broadband nature of real EEG signals. Simulation parameters: sampling rate = 500 Hz, duration = 10 s, embedding dimension m = 2, tolerance r = 0.2.



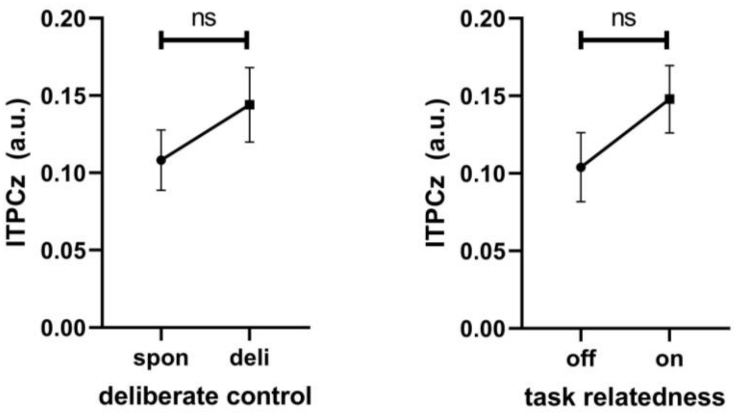
Supplementary Figure 4. Phase-Shuffled Pre-Stimulus FS and SE Across Thought Dimensions. Shown are the paired t-test comparisons of pre-stimulus FS and SE after phase shuffling for the two thought dimensions (task relatedness and deliberate control). No significant differences emerged between the thought dimensions under phase-shuffled conditions, emphasizing the role of phase-related mechanisms in determining the observed relationships. Note: ns: no significance.



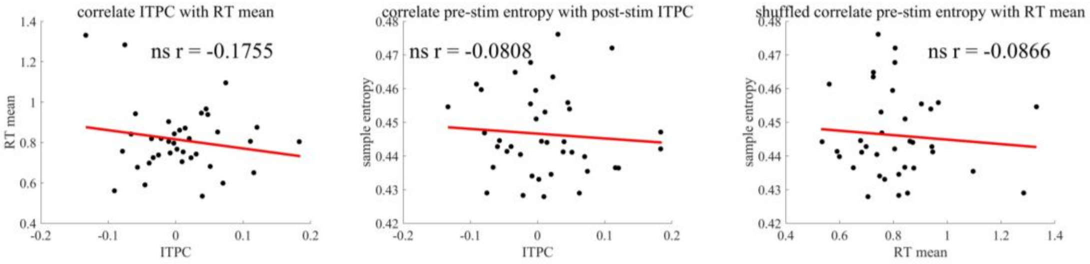
Supplementary Figure 5. Relationship of Pre-Stimulus Dynamics with Thought Dimensions in Resting-State Pseudo-Trials. Shown are the paired t-test comparisons of pre-stimulus FS and SE in resting-state pseudo-trials. No significant differences were observed between off-task and on-task thoughts or between spontaneous and deliberate thoughts under resting-state conditions. These findings suggest that the impact of the pre-stimulus dynamics on the two thought dimensions is specifically tied to the task context. Note: ns: no significance.



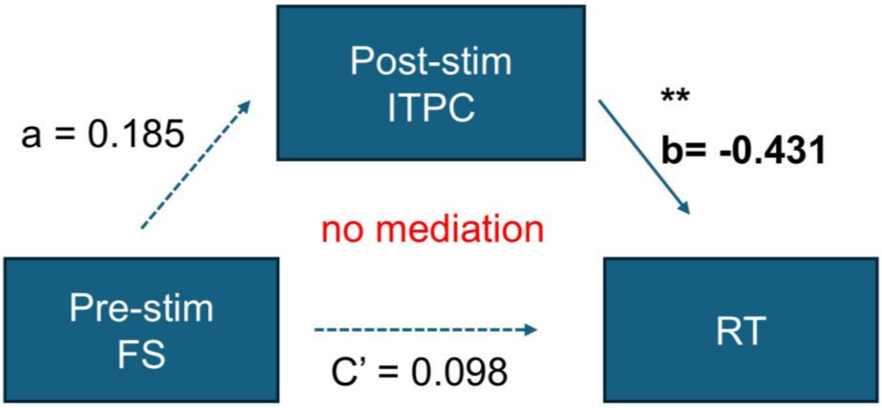
Supplementary Figure 6. Correlations Between Post-Stimulus ITPC in Delta/Theta Bands and RT. Shown are the Pearson correlation analyses between post-stimulus ITPC in the delta (1–4 Hz) and theta (4–7 Hz) bands with RT. No significant correlations were observed in either frequency band. Note: ns: no significance.



Supplementary Figure 7. Post-Stimulus Alpha ITPC Across Thought Dimensions. Shown are the paired t-test comparisons of post-stimulus alpha ITPC between off-task and on-task thoughts, as well as between spontaneous and deliberate thoughts. No significant differences were detected across either thought dimension. Note: ns: no significance.

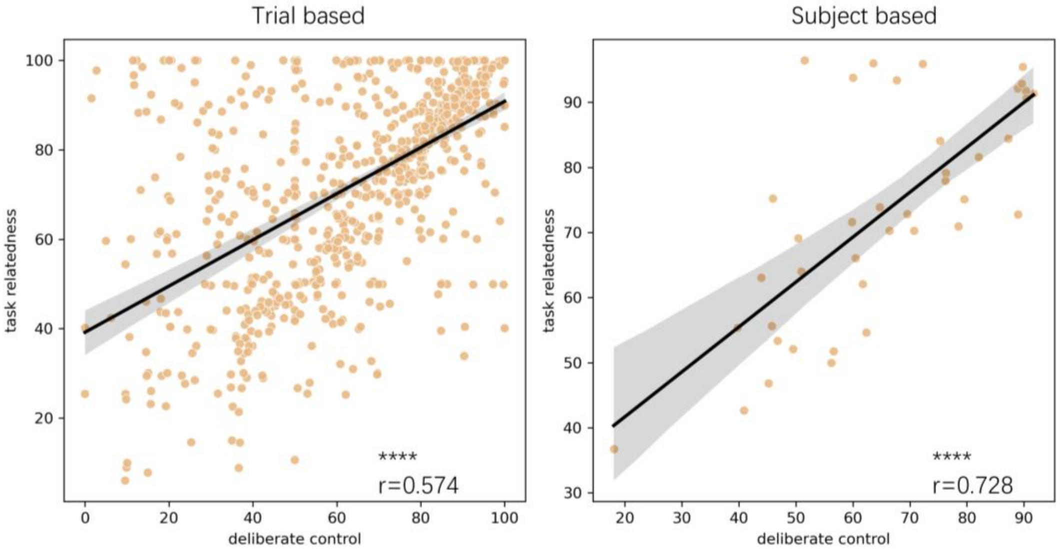


Supplementary Figure 8. Phase-Shuffled Controls for Post-Stimulus Alpha ITPC, Pre-Stimulus SE, and RT. Shown are the Pearson correlation analyses conducted on phase-shuffled data among post-stimulus alpha ITPC and RT, pre-stimulus SE and post-stimulus ITPC, as well as pre-stimulus SE and RT. No significant correlations were found under these phase-shuffled conditions, indicating the importance of phase-related processes in linking pre-stimulus dynamics with post-stimulus coherence and behavior.



Supplementary Figure 9. Mediation Model Among Pre-Stimulus FS, Post-Stimulus ITPC, and RT. Shown are the results of the mediation analysis examining pre-stimulus FS, post-stimulus ITPC, and RT. In contrast to SE, no significant mediation effect was observed when FS served as the predictor. This finding indicates that FS does not play a direct role in linking pre- and post-stimulus activity through ITPC. Note: **: p<0.01.

Supplementary Figure 10. Phase-Shuffled Mediation Models for Pre-Stimulus SE, FS, Post-Stimulus ITPC, and RT. Shown are the mediation models examining pre-stimulus SE and FS with post-stimulus ITPC and RT under phase-shuffled conditions. No significant mediation effects were observed, underscoring the importance of phase-related processes in linking pre- and post-stimulus activity.



Supplementary Figure 11. Relationship Between Deliberate Control and Task Relatedness in Resting-State. Shown are the Pearson correlations for the two thought dimensions (deliberate control, task relatedness) computed separately for trials and individuals in resting-state data. Note: ****: p<0.0001.

Details of calculations of peak frequency sliding

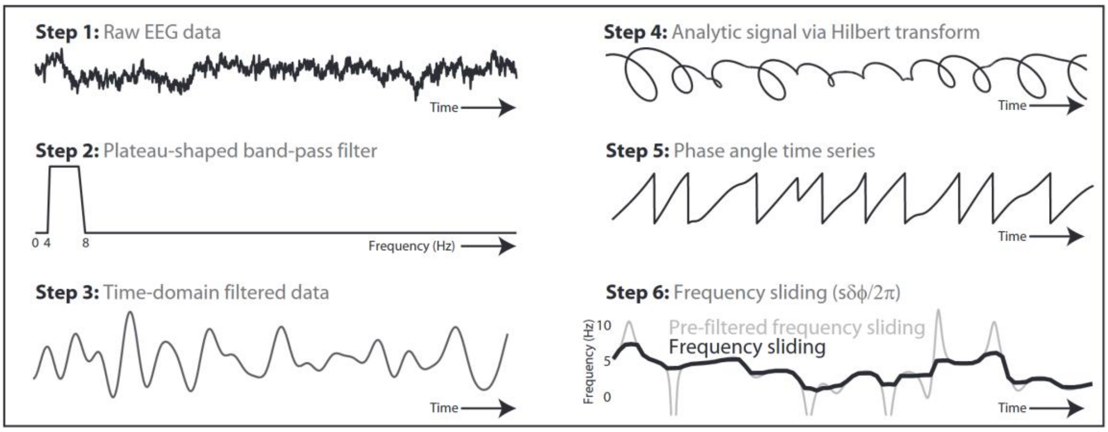


Figure adjusted from Cohen (2014b). Computation of frequency sliding.

Frequency sliding was computed following the procedure described by Cohen (2014b). Briefly, the EEG time series was first band-pass filtered within a predefined frequency range of interest (e.g., alpha and theta in our case). A Hilbert transform was then applied to the filtered signal to obtain the analytic representation, from which the instantaneous phase time series was extracted and unwrapped. Frequency sliding was defined as the first temporal derivative of the unwrapped phase angle, scaled by the sampling rate and normalized by 2π as shown in the function of

$$f(t) = \frac{s}{2\pi} \cdot \frac{d\phi(t)}{dt}$$

where s is the sampling rate and $\phi(t)$ is the instantaneous phase. This yields a continuous time series of instantaneous oscillation frequency.

To reduce non-physiological spikes caused by transient phase slips, a median filter with a window size of 10 data points was applied to the frequency sliding time series. Importantly, frequency sliding captures the moment-to-moment speed of an oscillation rather than its power. Higher frequency sliding values indicate faster oscillatory dynamics, while lower frequency sliding values indicate slower oscillatory dynamics.