Investigating Micro-Dynamic Neural Processing Patterns in Insight Problem Solving

Authors: Chen Yan, Li Ying, Liu Guanxiong, Yu Quanlei, Liang Zheng, Chen Shi, Zhao Qingbai, Liang Zheng, Chen Shi, Zhao Qingbai

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Abstract

This study employed EEG microstate analysis to investigate the micro-dynamic neural processing patterns of insight problem-solving in compound remote association tasks. The main findings indicated that during the early stage of problem presentation, both insight and non-insight solution conditions exhibited higher frequencies of microstate B (associated with visual processing) and increased transitions between microstate B and D (related to the executive function network) compared to the unsolved condition. Relative to the non-insight solution condition, insight solutions demonstrated higher frequencies of microstate C (associated with the default mode network) during the middle and later stages, as well as elevated mutual transition probabilities among microstate A (associated with sensory and auditory processing), C, and D. This study provides a preliminary examination of the micro-dynamic neural processing patterns underlying insight problem-solving, offering electrophysiological evidence for revealing the complex interactive processes among multiple cognitive activities under the regulation of executive function during insight problem-solving, and providing insights into how unconscious processing may change throughout the insight problem-solving process.

Full Text

Exploring the Micro-Dynamic Neural Processing Patterns of Insight Problem Solving

Yan Chen[1], Ying Li[1], Guanxiong Liu[1], Quanlei Yu[1], Zheng Liang[1],[2], Shi Chen[3],[4], Qingbai Zhao[1]

[1]Key Laboratory of Adolescent Cyberpsychology and Behavior (CCNU), Ministry of Education; Key Laboratory of Human Development and Mental Health of Hubei Province; School of Psychology, Central China Normal University,

Wuhan 430079, China
[2]Department of Psychological and Cognitive Sciences, Tsinghua University, Beijing 100084, China
[3]Hubei Health Industry Development Research Center, School of Medical Humanities, Hubei University of Chinese Medicine, Wuhan 430065, China
[4]Hubei Shizhen Laboratory, Wuhan 430000, China

Abstract

This study employed EEG microstate analysis to investigate the micro-dynamic neural processing patterns underlying insight problem solving in a Compound Remote Associates task. The main findings revealed that, during the initial problem presentation phase, both insight and non-insight solutions exhibited higher frequencies of microstate B (associated with visual processing) and more transitions between microstates B and D (related to executive function networks) compared to unsolved trials. In contrast, insight solutions during middle and late stages showed higher frequencies of microstate C (associated with the default mode network), along with elevated mutual transition probabilities among microstates A (linked to perceptual/auditory processing), C, and D. This study provides an initial examination of the micro-dynamic neural processing patterns in insight problem solving, offering electrophysiological evidence for the complex interplay of multiple cognitive activities under executive control during insight, and shedding light on how unconscious processing may evolve throughout the insight problem-solving process.

Keywords: insight problem solving, microstate, unconscious processing
Classification Code: B842

Problem solving represents a crucial adaptive mechanism through which individuals effectively apply existing knowledge and experience to changing situations. However, not all problems yield to established rules. Sometimes individuals encounter impasses until a solution suddenly emerges, accompanied by positive affective experiences—a phenomenon known as insight problem solving (Kohler, 1985). As a quintessential form of creative thinking, insight problem solving involves complex interactions among multiple cognitive processes (Haavold & Sriraman, 2022) and has attracted considerable attention from cognitive neuroscientists.

Like other forms of problem solving, insight problem solving encompasses general processes including problem comprehension, information search within the problem representation space using familiar strategies, solution generation, and solution evaluation (Haavold & Sriraman, 2022). During this process, information most directly relevant to the problem from an individual' s knowledge base becomes activated and spreads further based on the problem-solving progression. Figure-based problem solving relies on visual processing of stimulus physical features, primarily activating visual-spatial brain regions including parietal cortex, occipital cortex, posterior temporal cortex, and cerebellum (Rominger et al., 2018; Lu & Singer, 2023). Verbal problem solving primarily involves processing auditory or semantic information, eliciting activation in the middle temporal gyrus, superior temporal gyrus, and inferior frontal gyrus (Aziz-Zadeh et al., 2009; Qiu et al., 2010). These widely activated visual-spatial or auditory-semantic representations are then selected and integrated under executive control to meet problem-solving demands (Lin et al., 2022; Beaty et al., 2015; Lloyd-Cox et al., 2022).

Unlike logical, conscious problem solving, insight problem solving is considered a creative process difficult to verbalize. Individuals typically encounter mental impasses that prevent solution, and breakthroughs often occur when people are not even consciously aware they are thinking about the problem (Haavold & Sriraman, 2022). In this sense, the key process in insight problem solving is a phenomenon relative to conscious attention, during which individuals continue processing the problem but lack subjective awareness of their problem-solving attempts. This cognitive activity occurring below the threshold of consciousness is termed unconscious processing. Regarding the processing content of verbal insight problem solving, the brain may unconsciously engage in long-distance associative spreading based on problem words (Gilhooly, 2016; Dijksterhuis & Nordgren, 2006), exploration and combination of semantic memory (Gao & Zhang, 2014), inhibition of irrelevant information (Liu et al., 2023), activation and reorganization of effective information (Liu et al., 2024), ultimately forming novel connections and the sudden emergence of solutions (Zhao et al., 2017; Fleck & Kounios, 2009). Thus, unconscious processing holds significant importance for understanding insight problem solving, yet existing research offers limited description and investigation of this process.

Current literature has primarily employed distraction or probe tasks following mental impasses to examine the role of unconscious processing in insight problem solving (Leszczynski et al., 2017; Tan et al., 2015). While these studies provide behavioral support for unconscious processing facilitating insight, they neither directly nor indirectly measure the unconscious processing process itself, and real-world insights do not always occur in distracting contexts. In contrast, Beeman et al. (2004) investigated the insight process without distraction or probe tasks, directly observing EEG activity during Compound Remote Associates (CRA) task performance. Their findings revealed a burst of high-frequency (gamma-band) neural activity 0.30 seconds before insight solution generation, which they interpreted as reflecting the sudden transition from unconscious to conscious processing of insight-related cognitive operations. However, whether unconscious processing changes dynamically prior to this sudden transition remains unanswered by Beeman et al.' s study.

As described above, the insight problem-solving process can be conceptualized as a comprehensive temporal sequence comprising multiple complex components (Shen et al., 2018; Haavold & Sriraman, 2022). During the initial problem-solving phase, it primarily involves extraction, selection, and integration of multiple information types like other problem solving, including visual-spatial or auditory-semantic information. At the mental impasse stage, information processing shifts from supraliminal to subliminal processing. Immediately before insight solution, the brain completes integration and deployment of cognitive processes in complex, unconscious ways within a very short time. Since the natural insight problem-solving process is uncontrollable and insight solutions are sudden and transient (Luo, 2004; Benedek et al., 2019), measurement at a very fine temporal scale is required to understand how multiple cognitive processes rapidly change and combine to support insight problem solving.

Event-related potentials (ERP) have been widely used to investigate cognitive processes in insight problem solving. Previous research has explored potential specific components. For instance, the P2 component emerges during the mental impasse stage of insight problem solving, considered related to metacognition and reflecting early metacognitive regulation of subsequent attention allocation processes (Shen et al., 2012). Between 300-500 ms, insight problem solving elicits a negative ERP component (N320, N350, N380, N400) localized to the anterior cingulate cortex, reflecting greater cognitive conflict between old and new thinking patterns (Mai et al., 2004; Wang et al., 2009). In relatively later stages, insight problem solving has been observed to elicit a late positive component (LPC/P600) in right frontal and temporal regions, typically considered to reflect semantic information integration (Brouwer & Hoeks, 2013). In creative language tasks (including insight problem solving), this component is located in the parahippocampal gyrus or distributed in right temporal regions, believed to reflect formation of novel semantic associations (Zhao et al., 2015, Zhao et al., 2017). These results support stage and process theories of insight and provide electrophysiological evidence for key cognitive processes in insight problem solving. However, these studies primarily focus on chained processes in insight problem solving, such as from problem representation to mental impasse formation, or from impasse formation to mental set breaking, which cannot explain the fundamental view that insight problem solving is an iterative evolutionary process (Huang et al., 2019; Shen et al., 2018; Bilalić et al., 2021).

A recent study creatively employed Hidden Markov Models (HMM) to investigate iterative transitions between different hidden states during insight problem solving (Yu et al., 2022). This study divided continuous EEG signals during CRA task performance into seven brain state topographies representing different frequency bands, finding that brain states representing the alpha frequency band play an important role in insight problem solving, with this role changing dynamically over the problem-solving time course. This study reconfirmed previous claims about the critical role of the alpha frequency band in insight problem solving (Fink et al., 2009; Zhou et al., 2018) and described the temporal dynamic relationship between frequency bands and solution strategies/processes. However, this study did not reveal the correspondence between these states and brain regions or networks related to insight problem solving, preventing more intuitive interpretation of the cognitive processes and interactions involved.

EEG microstate analysis can serve as a tool to address these issues. Beyond the temporal advantages of EEG itself, this method can provide certain spatial information. The microstate principle posits that spontaneous brain activity is not entirely continuous and random, but can be divided into discrete topographies with certain cognitive significance within relatively short time periods (Lehmann et al., 1987; Koenig et al., 2002; Lehmann et al., 2009). Microstate analysis is typically divided into task-state analysis and resting-state analysis. Task-state analysis is usually combined with event-related potentials. After identifying ERP components, microstate time series of different components can be analyzed to investigate stability and other characteristics of ERP components during specific cognitive processes (Schiller et al., 2016). Resting-state analysis clusters all time points into several categories (most commonly 4 to 6 categories) and represents them as time series. Overall, the topographies formed by these clusters are highly similar across studies and can explain approximately 65%~85% of EEG activity. Research has found certain correspondences between microstate topographies and large-scale resting-state brain networks obtained from functional magnetic resonance imaging (fMRI). For example, microstate A is a right frontal-to-left posterior topography with source localization primarily showing activation in temporal cortex and auditory networks (Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017). Microstate B shows a right frontal-to-left posterior topography (Koenig et al., 2002) and is clearly observed in activities involving visual-spatial and imagery processing (Britz et al., 2010; Custo et al., 2017). Microstate C is an anterior-posterior relatively symmetrical topography reflecting internal mental activity, self-reflection, and attentional disengagement from the task, being more active during task-free states (Zanesco et al., 2021; Bréchet et al., 2019; Custo et al., 2017; Croce et al., 2018). Microstate D shows a frontocentral maximum topography associated with executive function and attentional control, being more prominent during cognitive tasks (Britz et al., 2010; Michel et al., 2024). These patterns maintain considerable consistency across different age groups, consciousness states, and even pathological conditions (Britz, 2010; Musso, 2010; Betzel, 2012). It should be noted that known topographical patterns include but are not limited to the above categories, requiring further analysis and judgment based on data clustering. Some studies have also applied resting microstate analysis to task-initiated spontaneous thinking, comparing microstates elicited by autobiographical memory and computational tasks (Bréchet et al., 2019). Such studies appropriately expand the application scope of resting microstates, facilitating investigation of dynamic organization of brain networks in millisecond-level time series, particularly for tasks requiring long-term guided spontaneous thinking like insight problem solving.

Although both HMM and microstates separate continuous neural imaging data into discrete brain states, they differ in the questions they can address. HMM essentially focuses on the relationship between time and state changes, revealing temporal dynamics of states. Microstates (especially resting-state microstates) enumerate the most likely states within a given time window, emphasizing how states and their corresponding cognitive processes manifest and interact. Resting-state microstate topographies show relative stability across studies and have been linked to specific cognitive activities. Although temporal structure cannot be compared with HMM, the connection between microstates and cognitive activities is more direct, which is more beneficial for understanding tasks like insight problem solving that involve complex cognitive processes. Additionally, transition probability metrics better describe interaction patterns between states. Specifically, the default mode network has been considered in previous fMRI studies to represent unconscious processing involving attentional disengagement from the current task during insight problem solving (Darsaud et al., 2011; Ritter & Dijksterhuis, 2014), while microstate C reflects part of the default mode network. Its parameters show significant positive correlation with alpha band activity (Hill et al., 2023), and the alpha band is precisely the frequency band reported to play an important role in previous insight problem solving research (Yu et al., 2022; Fink et al., 2009). Furthermore, the association pattern between microstate C during mind wandering and microstates D and E during focused task states resembles the interaction between anticorrelated networks (e.g., default mode network and executive control network, salience network) in fMRI research (Zanesco et al., 2021). Therefore, this may provide a window to explore the role of unconscious processing in insight problem solving and its dynamic changes.

This study applied EEG microstate analysis to investigate brain activity during CRA task performance, aiming to clarify cognitive processes that may exist in insight problem solving, such as basic perceptual processing and executive functions, and whether brain states potentially representing unconscious processing appear specifically during insight problem solving. Furthermore, it examined how cognitive processes reflected by brain states interact during problem solving. Specifically, the study recorded EEG activity while participants attempted to solve CRA problems and used microstates to interpret topographic differences across three time stages (initial problem presentation, solution process, response execution) for different solution types (insight, non-insight, and unsolved). Given the open-ended and multidimensional nature of insight problem solving, this study first aimed to describe which cognitive processes participate in multiple stages of insight problem solving. As a form of problem solving, we expected insight problem solving to require executive function involvement, possibly manifested as longer mean duration, higher occurrence frequency, and more frequent transitions of microstate D with other states. Second, compared to non-insight problem solving, insight problem solving involves unconscious processing, thus may show longer mean duration, higher occurrence frequency, and more transitions with other states for microstate C during problem solving. Additionally, given Beeman et al. (2004) reported that approximately 0.30 seconds before problem solving, compared to non-insight solutions, insight solutions showed sudden gamma-band enhancement at right anterior temporal electrodes, which they interpreted as representing the sudden transition from unconscious to conscious states during insight problem solving, this study will verify the stability of this result and examine whether similar neural response patterns exist in insight problem solving.

2.1 Participants

Assuming an effect size of 0.25, alpha level of 0.05, and statistical power of 0.80, G*Power calculated that the total sample size for repeated measures ANOVA was 15. Considering previous research using CRA tasks indicates the task is challenging (Bowden & Beeman, 2003; Beeman et al., 2004; Yu et al., 2022), to ensure sufficient sample size for subsequent statistical analysis, this study recruited as many participants as possible (42). The experimenter then reviewed participants' English proficiency qualifications (IELTS\$ $7orTOEFL\ 95ormajoringinEnglishwithgrades$ \$80) and required participants to complete a self-assessment questionnaire—the Chinese Standards of English Language Ability Questionnaire (Pan et al., 2019). Ultimately, 37 right-handed Chinese native speakers with English as their second language (mean age 21.20 years, 17 females) met the requirements and voluntarily participated in the experiment. All participants were informed about the experimental procedure before the formal experiment and signed informed consent forms, receiving corresponding compensation after completion. It should be noted that although this was an English experiment, it only involved word-level processing. The recruited L2 participants' English proficiency far exceeded task demands.

2.2 Experimental Materials

The Compound Remote Associates (CRA) test was used as experimental material (Bowden & Beeman, 2003). This test presents three words on screen (e.g., cottage, swiss, cake) and requires participants to generate an answer word that can combine with each given word to form a phrase or compound word (e.g., cheese: swiss cheese, cheese cake, cottage cheese). This material has been widely used to explore verbal insight problem solving (Beeman et al., 2004; Yu et al., 2022).

2.3 Experimental Procedure

Before the experiment, the experimenter explained the criteria for "insight solutions" and "non-insight solutions" to participants. These criteria were based on definitions of the two solution types in previous insight research to ensure participants clearly understood what each solution type represented (Danek et al., 2014; Jung-Beeman et al., 2004). It should be noted that in relatively early insight problem solving research, a certain type of difficult problem was directly designated as an insight problem, and successful solution of such problems was considered insight. This method of equating solution of a certain problem type with insight is unreasonable because not all problem solvers have similar knowledge experiences and solution approaches. Therefore, a relatively difficult problem might trigger insight experiences in some solvers but not others. Consequently, this study first used a more common recent method to classify insight vs non-insight based on participants' subjective reports. Given that this study did not instruct participants to preferentially select a particular strategy, we considered it acceptable to solve problems through different strategies and objectively evaluate their subjective experiences. The experiment was programmed using E-prime 2.0 software. First, "Ready?" was displayed on screen for 1s, followed by a 1s blank screen to focus participants' attention. Participants then saw three problem words presented simultaneously on screen and were required to generate an answer word that could form a familiar compound word or phrase with each of the three problem words. Each problem had a maximum solution time of 15s. Based on previous research, this duration can balance response accuracy and reaction time well with many trials (Erickson et al., 2018; Yu et al., 2022). When participants thought of an answer, they should immediately press the "K" key, after which "Solution?" appeared on screen. Participants verbally reported their answer, recorded by the experimenter, and used mouse left/right buttons to report their solution method (insight/non-insight), with button assignment counterbalanced across participants. The experimental flow is shown in Figure 1 [Figure 1: see original paper], where "S" indicates stimulus onset and "R" indicates when participants needed to respond within 15s after stimulus presentation. Trials without responses were marked as unsolved, and the program automatically jumped to a 1s fixation cross after stimulus presentation exceeded 15s, then began the next trial. The experiment included 10 practice trials and 134 formal trials. The experimenter confirmed participants understood the task and could correctly classify insight vs non-insight solutions during practice trials before starting the formal experiment.

2.4 Data Acquisition and Preprocessing

EEG data were recorded using a BrainAmp MR64 system (Brain Products GmbH, Munich, Germany) with an elastic cap containing 64 electrodes positioned according to the extended international 10-20 system. Ground electrode GND and online reference electrode REF were located at AFz and FCz, respectively. Data were sampled at 500Hz. Data preprocessing was conducted using the eeglab toolbox version 2024.0 running on MATLAB 2023b. Channel locations were initially identified and unused electrodes were removed. Subsequently, data were processed using the Harvard-developed preprocessing pipeline HAPPE (Lopez et al., 2022) (GitHub-PINE-Lab/HAPPE: EEG Pre-Processing Pipeline). Specifically, data were downsampled to 250Hz, bandpass filtered at 1-40Hz, and notch filtered (Cleanline) to remove 50Hz line noise. Bad channels and artifacts were detected, rejected channels were interpolated, and offline re-referencing to the global average was performed. Data segments identified as artifacts were deleted. After organizing reaction times for all response trials, continuous data were segmented based on participants' average reaction times under the two solution conditions to extract time windows of interest: (1) T1: 0 to 2s after problem onset; (2) T2: 2 to 5s after problem onset; (3) T3: 1s before to 0.5s after button press. This division was based on previous research to focus on neural activity within time windows where cognitive processes could be more confidently identified (Beeman et al., 2004; Yu et al., 2022). Trials with reaction times less than 6s were excluded to avoid overlapping sampling between stages. An amplitude threshold of $±$100 V was used as the criterion for wavelet threshold denoising, and independent component analysis (ICA) was used to remove artifacts from segmented data. Finally, data were visually inspected, and artifacts were marked and excluded from further analysis.

2.5 Microstate Analysis

This study adopted the method of Bréchet et al. (2019), using resting-state EEG microstate methods to analyze task-initiated spontaneous thinking to observe temporal dynamics of microstate topographies representing specific mental activities during verbal insight problem solving. This study used the eeglab microstate analysis toolbox (Poulsen et al., 2018) (https://github.com/atpoulsen/microstate-eeglab-Toolbox) based on the MATLAB programming platform. This toolbox is fully transparent in all analysis steps, allows integration of any clustering algorithm, and includes a series of functions that can be used independently, modified, or combined as interactive plugins into widely used open-source EEG analysis software (Delorme & Makeig, 2004).

Specifically, clustering methods available for microstate analysis mainly include AAHC, TAAHC, and k-means. Given that the first two methods' clustering results are relatively affected by the quality of randomly selected templates, this study used k-means clustering to determine the optimal number of clusters explaining the maximum global explained variance (GEV) in voltage time series. This method is also the most frequently used clustering method in microstate analysis (Tarailis et al., 2024). K-means typically requires pre-setting the number of clusters, then dividing EEG data into a fixed number of clusters. EEG data are then repeatedly reassigned to existing clusters under iteration, and GEV of clustering results is calculated until optimal cluster assignment is achieved. In this study, 4-6 initial topographic categories were set, and GFP peak clustering method was used to treat topographies at time points with highest signal-to-noise ratio as unique topographies within given time periods. Optimal cluster number was selected by comparing GEV of 4-6 topographies. After microstate analysis was performed for each participant under each condition, individual cluster topographic templates or grand mean cluster topographic templates needed to be selected. Grand mean templates measure all data content with the same pattern, but this pattern may not be entirely suitable for exploring individual data characteristics. Individual templates can better restore detailed features of individual data, but microstate topographic patterns may vary considerably across participants, potentially causing difficulties in cross-participant comparisons. This study aimed to investigate cognitive processes in problem solving; individual differences were not the focus. Therefore, this study selected grand mean templates, using four topographies formed by group-level clustering as templates for back-fitting to all participants' data. To investigate how these microstate categories might reflect cognitive processes (Koenig et al., 2002; Tarailis et al., 2024; Michel et al., 2024; Khanna et al., 2015) and how they interact, statistical analyses of microstate temporal parameters (mean duration, occurrence frequency, and transition probability) were conducted using SPSS 27.0.

2.6 Time-Frequency Analysis

To verify findings from previous similar studies, this study further examined time-frequency signal differences across different problem-solving conditions. Time-frequency analysis and subsequent statistical tests were performed using the FieldTrip toolbox in MATLAB. Time-frequency analysis used wavelet (Morlet wavelet-based) algorithm (Oostenveld et al., 2011) to calculate neural oscillation power from 1-40Hz with 4ms sampling steps, extracting data from 3s before to 1s after response, with baseline correction using the period from 2s to 1s before response (baseline correction method: dB conversion). Wavelet width was 5. Guided by Beeman et al. (2004) results, time-frequency results from 0.5s to 0.3s before response were focused on. The reason for selecting the -2s to -1s window as baseline was considering the instability of values closest to data segment edges during time-frequency analysis. Therefore, to avoid contamination between data segments, appropriately moving away from edge values helps circumvent mutual contamination issues (Wang et al., 2023; Yue et al., 2020). Additionally, to evaluate stimulus-induced non-phase-locked oscillatory activity, individual trial time-frequency responses were calculated separately and averaged in subsequent statistical analyses. In statistical analysis, to avoid multiple comparison problems, this study used cluster-based permutation tests (non-parametric cluster-based permutation test) to verify whether gamma-band signal energy differed between insight and non-insight conditions at temporoparietal electrode sites TP7, TP8, P7, P8 within the -0.50 to -0.30s time range (time range and ROI selection referenced Beeman et al., 2004). Specifically, T-test values (two-tailed, 0.025 significance level) between energy at each frequency and time point across the two conditions served as statistics. Cluster statistics (mass) random distribution was obtained through 5000 Monte Carlo simulations. Clusters were defined as adjacent time-frequency points, and maxsize algorithm was used for determination. Cluster-corrected significance level was set at 0.05, meaning when cluster statistic size from original data ranked in the top 0.05 of random distribution, the cluster was considered significant, indicating significant difference between conditions.

3. Results

3.1 Behavioral Results

Data from 12 participants were excluded (2 participants with excessive artifacts, 10 participants with insufficient valid trials per condition, $ $10 trials). Thus, subsequent analysis included data from 25 participants. After excluding incorrect responses, each participant averaged 109.36 trials (sd=15.92), including

40.88 unsolved trials (sd=25.40), 31.68 insight trials (sd=17.44), and 36.80 non-insight trials (sd=14.37). The overall mean accuracy rate was 51% (sd=13%), with insight solution accuracy at 83% (sd=14%) and non-insight solution accuracy at 70% (sd=14%). Insight solution accuracy was significantly higher than non-insight solution accuracy, $t(24) = 4.93$, $p < 0.001$, Cohen' s d = 0.97. Mean reaction time for insight solutions was 8136.97ms (sd=1664.90ms), and for non-insight solutions was 8992.42ms (sd=1134.21ms). Non-insight solution reaction time was significantly longer than insight solution reaction time, $t(24)=3.22$, $p=.004$, Cohen' s d=0.65. These results are similar to previous findings with English native speakers using the same materials. Bowden and Beeman (2003) reported an average solution rate of approximately 50.50% within a 15s time limit; this study' s average solution rate within 15s was 51.10%. Another study included 127 trials for analysis, with an average of 81 unsolved trials, 26 insight trials, and 20 non-insight trials (Yu et al., 2022), similar to this study. From behavioral results, Chinese native speakers' task performance fully met task requirements.

3.2 Microstate Results

This study generated a global explained variance (GEV) across different conditions and solution stages. To consider overall circumstances, we averaged GEV across different stages within conditions, then averaged across conditions, obtaining overall mean GEV for 4, 5, and 6 topographies. Among clustering results of 4-6 topographies, 4-topography microstates showed best data fit (GEV=71.47%), 5-topography microstates showed GEV=68.75%, and 6-topography microstates showed GEV=67.33%. Therefore, all subsequent analyses were based on 4 microstates. Figure 2 [Figure 2: see original paper] shows microstate time series for one participant during problem presentation stage (T1) under insight solution and unsolved conditions. Repeated measures ANOVA was then conducted on mean duration, occurrence rate, and transition probability of microstate clustering across three answer types.

3.2.1 Mean Duration Repeated measures ANOVA results showed that the main effect of answer type (insight, non-insight, unsolved) was not significant, $F(2,48)=3.00$, $p=.059$. The main effect of time window (T1—initial problem presentation, T2—problem solving process, T3—response stage) was significant, $F(2,48)=7.61$, $p=.001$, $^2=0.24$. The main effect of microstate type (microstate A, B, C, D) was significant, $F(3,72)=3.03$, $p=0.035$, $^2=0.11$ (Table 1).

Table 1 Interaction effects on mean duration across conditions

Interaction	p-value
Answer type × Time window	<0.001
Answer type × Microstate	<0.001
Time window × Microstate	<0.001
Answer type × Time window × Microstate	<0.001

Interaction	p-value

The interaction between answer type and time window was not significant, $F(4,96)=1.13$, $p=0.346$. The interaction between answer type and microstate was significant, $F(6,144)=5.92$, $p<0.001$, $^2=0.20$. The interaction between microstate and time window was significant, $F(6,144)=15.48$, $p<0.001$, $^2=0.39$. The three-way interaction between answer type, time window, and microstate was significant, $F(12,288)=11.56$, $p<0.001$, $^2=0.33$ (Figure 3 [Figure 3: see original paper]). Simple simple effects analysis showed that during problem presentation stage (T1), mean duration of microstate A under unsolved condition was significantly longer than under insight condition ($p=0.002$) and non-insight condition ($p=0.003$). Mean duration of microstate B under insight condition was significantly longer than under unsolved condition ($p<.001$), and mean duration of microstate B under non-insight condition was significantly longer than under unsolved condition ($p=0.002$). Mean duration of microstate D under non-insight condition was significantly longer than under unsolved condition ($p=0.04$). During problem solving stage (T2), mean duration of microstate A under both insight ($p<0.001$) and non-insight ($p=0.026$) conditions was significantly longer than under unsolved condition, while mean duration of microstate B under both insight ($p=0.027$) and non-insight ($p=0.03$) conditions was significantly shorter than under unsolved condition. During response stage (T3), mean duration of microstate A under insight condition was longer than under non-insight condition ($p=0.016$) and unsolved condition ($p<0.001$). Mean duration of microstate A under non-insight condition was longer than under unsolved condition ($p=0.007$). Mean duration of microstate B under non-insight condition was longer than under insight condition ($p<0.001$), and mean duration of microstate B under unsolved condition was longer than under insight condition ($p<0.001$).

3.2.2 Occurrence Frequency Repeated measures ANOVA results showed that the main effect of answer type was significant, $F(2,48)=3.45$, $p=0.039$, $^2=0.13$. The main effect of time window was significant, $F(2,48)=8.35$, $p<0.001$, $^2=0.26$. The main effect of microstate was significant, $F(3,72)=7.76$, $p<0.001$, $^2=0.24$ (Table 2).

Table 2 Interaction effects on occurrence frequency per second across conditions

Interaction	p-value
Answer type × Time window	<0.001
Answer type × Microstate	<0.001
Time window × Microstate	<0.001
Answer type × Time window × Microstate	<0.001

The interaction between answer type and time window was not significant, $F(4,96)=1.16$, $p=0.336$. The interaction between answer type and microstate was significant, $F(6,144)=11.55$, $p<0.001$, $^2=0.33$. The interaction between time window and microstate was significant, $F(6,144)=16.20$, $p<0.001$, $^2=0.40$. The three-way interaction between answer type, time window, and microstate was significant, $F(12,288)=8.28$, $p<0.001$, $^2=0.26$ (Figure 4 [Figure 4: see original paper]). Simple simple effects analysis showed that during problem presentation stage, occurrence frequency of microstate A under unsolved condition was significantly higher than under insight condition ($p<0.001$) and non-insight condition ($p=0.001$). Occurrence frequency of microstate B under insight condition was significantly higher than under unsolved condition ($p=0.004$), and occurrence frequency of microstate B under non-insight condition was significantly higher than under unsolved condition ($p=0.002$). Occurrence frequency of microstate C under unsolved condition was significantly higher than under insight condition ($p=0.014$) and non-insight condition ($p=0.014$). Occurrence frequency of microstate D under insight condition was significantly higher than under unsolved condition ($p=0.009$), while occurrence frequency of microstate D under non-insight condition was significantly higher than under insight condition ($p=0.001$). During problem solving stage, occurrence frequency of microstate A under insight condition was significantly higher than under non-insight condition ($p=0.005$), occurrence frequency of microstate A under non-insight condition was significantly higher than under unsolved condition ($p=0.001$), and occurrence frequency of microstate B under non-insight condition was higher than under insight condition ($p=0.009$). Occurrence frequency of microstate C under insight condition was higher than under non-insight condition ($p=0.006$), and occurrence frequency of microstate C under unsolved condition was higher than under non-insight condition ($p<0.001$). During response stage, occurrence frequency of microstate A under insight condition was significantly higher than under non-insight condition ($p=0.017$), occurrence frequency of microstate B under non-insight condition was significantly higher than under insight condition ($p<0.001$), and occurrence frequency of microstate B under unsolved condition was significantly higher than under insight condition ($p=0.009$). Occurrence frequency of microstate C under insight condition was higher than under non-insight condition ($p<0.001$), and occurrence frequency of microstate C under unsolved condition was higher than under non-insight condition ($p<0.001$).

3.2.3 Transition Probability from Microstate A to Other Microstates

Repeated measures ANOVA showed that the main effect of answer type was significant, $F(2,48)=4.01$, $p=0.040$, $^2=0.143$. The main effect of time window was significant, $F(2,48)=27.17$, $p<0.001$, $^2=0.53$. The main effect of transition type (microstate A→B, A→C, A→D) was significant, $F(3,72)=12.07$, $p<0.001$, $^2=0.34$ (Table 3).

Table 3 Interaction effects on transition probability from microstate A to other microstates

Interaction	p-value
Answer type × Time window	<0.001
Answer type × Transition type	<0.001
Time window × Transition type	<0.001
Answer type × Time window × Transition type	<0.001

The interaction between answer type and time window was significant, F(4,96)=13.98, p<0.001, ^{2}=0.37. The interaction between answer type and transition type was significant, F(4,96)=12.00, p<0.001, ^{2}=0.33. The interaction between time window and transition type was significant, F(4,96)=7.79, p<0.001, ^{2}=0.25. The three-way interaction between answer type, time window, and transition type was significant, F(8,192)=3.76, p<0.001, ^{2}=0.14 (Figure 5 [Figure 5: see original paper]). Simple simple effects analysis showed that during problem presentation stage, PA-C (P indicates probability, PA-C indicates transition probability from microstate A to microstate C, and so on) under unsolved condition was higher than under insight condition (p<0.001) and non-insight condition (p<0.001). During problem solving stage, PA-B (p=0.002) and PA-D (p=0.009) under non-insight condition were significantly higher than under unsolved condition, while PA-C under insight condition was significantly higher than under non-insight condition (p=0.036). During response stage, PA-B under non-insight condition was significantly higher than under insight condition (p<0.001) and unsolved condition (p=0.004). PA-C under insight condition was significantly higher than under non-insight condition (p<0.001) and unsolved condition (p=0.029). PA-D under insight condition was significantly higher than under unsolved condition (p=0.011), while PA-D under non-insight condition was significantly higher than under unsolved condition (p=0.013).

3.2.4 Transition Probability from Microstate B to Other Microstates

Repeated measures ANOVA results showed that the main effect of answer type was significant, F(2,48)=15.56, p<0.001, ^{2}=0.39. The main effect of time window was significant, F(2,48)=25.73, p<0.001, ^{2}=0.52. The main effect of transition type was significant, F(2,48)=9.77, p<0.001, ^{2}=0.29 (Table 4).

Table 4 Interaction effects on transition probability from microstate B to other microstates

Interaction	p-value
Answer type × Time window	<0.001
Answer type × Transition type	<0.001
Time window × Transition type	<0.001
Answer type × Time window × Transition type	<0.001

The interaction between answer type and time window was significant, F(4,96)=12.14, p<0.001, ^{2}=0.34. The interaction between answer type and transition type was significant, F(4,96)=7.20, p<0.001, ^{2}=0.23. The interaction between time window and transition type was significant, F(4,96)=11.82, p<0.001, ^{2}=0.33. The three-way interaction between answer type, time window, and transition type was significant, F(8,192)=2.34, p=0.048, ^{2}=0.09 (Figure 6 [Figure 6: see original paper]). Simple simple effects analysis showed that during problem presentation stage, PB-D under insight condition (p=0.002) and non-insight condition (p=0.004) were significantly higher than under unsolved condition. During problem solving stage, PB-A under non-insight condition was significantly higher than under unsolved condition (p=0.010). PB-C under unsolved condition was significantly higher than under insight condition (p=0.014) and non-insight condition (p=0.002). PB-D under non-insight condition was significantly higher than under insight condition (p=0.013). During response stage, PB-A under non-insight condition was significantly higher than under insight condition (p=0.003) and unsolved condition (p=0.032). PB-C under unsolved condition was significantly higher than under insight condition (p=0.010) and non-insight condition (p=0.005). PB-D under non-insight condition was significantly higher than under insight condition (p=0.003).

3.2.5 Transition Probability from Microstate C to Other Microstates

Repeated measures ANOVA results showed that the main effect of answer type was significant, F(2,48)=22.23, p<0.001, ^{2}=0.48. The main effect of time window was significant, F(2,48)=13.94, p<0.001, ^{2}=0.37. The main effect of transition type was significant, F(2,48)=8.22, p<0.001, ^{2}=0.26 (Table 5).

Table 5 Interaction effects on transition probability from microstate C to other microstates

Interaction	p-value
Answer type × Time window	<0.001
Answer type × Transition type	0.777
Time window × Transition type	<0.001
Answer type × Time window × Transition type	<0.001

The interaction between answer type and time window was significant, F(4,96)=3.51, p=0.028, ^{2}=0.13. The interaction between answer type and transition type was not significant, F(4,96)=0.04, p=0.777. The interaction between time window and transition type was significant, F(4,96)=10.96, p<0.001, ^{2}=0.31. The three-way interaction between answer type, time window, and transition type was significant, F(8,192)=6.87, p<0.001, ^{2}=0.22 (Figure 7 [Figure 7: see original paper]). Simple simple effects analysis showed that during problem presentation stage, PC-A under unsolved condition was higher than under insight condition (p=0.001) and non-insight condition (p<0.001). PC-B under insight condition was higher than under non-insight condition ($p=0.043$). During problem solving stage, PC-A under insight condition was higher than under non-insight condition ($p=0.014$). PC-B under unsolved condition was higher than under insight condition ($p=0.013$) and non-insight condition ($p=0.003$). PC-D under insight condition was higher than under non-insight condition ($p=0.040$), and PC-D under unsolved condition was higher than under non-insight condition ($p<0.001$). During response stage, PC-A under insight condition was higher than under non-insight condition ($p=0.002$). PC-D under insight condition was higher than under non-insight condition ($p=0.004$), and PC-D under unsolved condition was higher than under non-insight condition ($p<0.001$).

3.2.6 Transition Probability from Microstate D to Other Microstates

Repeated measures ANOVA results showed that the main effect of answer type was significant, $F(2,48)=3.40$, $p=0.042$, $^{2}=0.124$. The main effect of time window was not significant, $F(2,48)=2.39$, $p=0.103$. The main effect of transition type was not significant, $F(2,48)=2.73$, $p=0.076$ (Table 6).

Table 6 Interaction effects on transition probability from microstate D to other microstates

Interaction	p-value
Answer type × Time window	<0.001
Answer type × Transition type	<0.001
Time window × Transition type	<0.001
Answer type × Time window × Transition type	<0.001

The interaction between answer type and time window was significant, $F(4,96)=3.24$, $p=0.038$, $^{2}=0.12$. The interaction between answer type and transition type was significant, $F(4,96)=9.73$, $p<0.001$, $^{2}=0.29$. The interaction between time window and transition type was significant, $F(4,96)=21.97$, $p<0.001$, $^{2}=0.48$. The three-way interaction between answer type, time window, and transition type was significant, $F(8,192)=8.44$, $p<0.001$, $^{2}=0.26$ (Figure 8 [Figure 8: see original paper]). Simple simple effects analysis showed that during problem presentation stage, PD-B under insight condition was higher than under unsolved condition ($p<0.001$), and PD-B under unsolved condition was higher than PD-A under unsolved condition ($p<0.001$). During problem solving stage, PD-A under insight condition was higher than under unsolved condition ($p=0.033$). PD-A under unsolved condition was higher than PD-B under unsolved condition ($p=0.004$). PD-B under unsolved condition was higher than under insight condition ($p<0.001$). PD-B under unsolved condition was higher than under insight condition ($p=0.004$). PD-C under insight condition was higher than under non-insight condition ($p=0.028$), and PD-C under unsolved condition was higher than under non-insight condition ($p=0.040$). During response stage, PD-A under insight condition was higher than under unsolved condition ($p=0.012$), and PD-A under non-insight condition was higher than under unsolved condition (p=0.015). PD-B under non-insight condition was higher than under insight condition (p=0.003). PD-C under insight condition was higher than under non-insight condition (p=0.002), and PD-C under unsolved condition was higher than under non-insight condition (p=0.004).

3.3 Time-Frequency Analysis

Cluster-based permutation tests showed that compared to non-insight problem solving, insight problem solving exhibited significantly enhanced gamma-band energy at right temporoparietal electrode P8, with cluster mass sum[t]=118, significance level p=0.02. The significant cluster' s temporal range was approximately -0.50~-0.45s. Two clusters were also found at left temporoparietal electrode P7, but they were not significant after statistical correction (Cluster 1 mass: sum[t]=37, p=0.13; Cluster 2 mass: sum[t]=8, p=0.23). One cluster existed at TP7, not significant after correction, cluster mass sum[t]=3, p=0.25. No clusters existed at TP8 (Figure 9 [Figure 9: see original paper], supplementary figure).

4. Discussion

To explore interactions among multiple cognitive processes during insight problem solving, this study analyzed EEG microstates under different solution conditions using the Compound Remote Associates (CRA) task, focusing on how neural indicators potentially related to unconscious processing develop during spontaneous insight problem solving and how they interact with multiple potential cognitive activities. Results showed that successful problem solving had strong neural associations with microstate D (topography considered related to executive function), while insight problem solving in middle and late stages contained more microstate C (topography reflecting part of the default mode network) than non-insight problem solving. The default mode network is a large-scale brain network with extensive nodes (Liu et al., 2022) that may be related to cognitive processes such as autobiographical memory, emotional processing, and unconscious processing, but its specific role depends on task demands and research purposes. For example, in tasks requiring recall of specific memories from photographs, activation patterns of default mode network-related microstate C may relate to autobiographical or episodic memory (Bréchet et al., 2019). When studying discrete emotional experiences, microstate C may reflect default mode network processing, evaluation, and construction of complex emotional experiences (Satpute & Lindquist, 2019). Microstate C found in sustained attention response tasks may reflect mind wandering and unconscious states (Croce et al., 2018; Zanesco et al., 2021). According to relevant theories and existing research on insight problem solving processes, the solution process may involve less autobiographical memory, episodic memory, or emotional processing. Therefore, we speculate that microstate C results in this framework more likely reflect participants' unconscious processing of the problem.

Our findings echo previous research on the roles of executive function network and default mode network in creative thinking (Lin et al., 2022; Beaty et al., 2015; Lloyd-Cox et al., 2022) and verify Beeman et al.' s (2004) reported gamma burst immediately before insight problem solving. Furthermore, they describe how multiple cognitive processes interact during the temporal sequence of insight problem solving, providing electrophysiological evidence for the association between unconscious processing and insight problem solving.

Consistent with microstate types reported in several previous studies (Britz et al., 2010; Croce et al., 2018; Pan et al., 2020; Tarailis et al., 2024), this study identified four microstate topographies with optimal fit through data-driven methods. Based on statistically significant results, schematic diagrams of microstate processing patterns under three answer types were drawn (Figure 10 [Figure 10: see original paper]), including occurrence frequencies and transition probability information of four typical microstates across different time windows.

4.1 Neural Processing Patterns in Unsolved Condition

Compared to both successful solution conditions, unsolved condition showed significantly higher occurrence frequency of microstate C across all three time windows, with significance level increasing along the problem-solving time course. Previous research reported microstate C activity in regions related to the default mode network, indicating its association with task-negative thoughts, mind wandering, self-related thinking, and emotional and interoceptive processing (Bréchet et al., 2019; Custo et al., 2017; Croce et al., 2018; Zanesco et al., 2021). Combining microstate C' s psychological function with our experimental task conditions, the dominant position of microstate C across three time windows may indicate that one major factor preventing problem solution is participants' lack of top-down attentional resource investment in the problem. Additionally, microstate A is primarily related to auditory and visual processing and individual arousal, with neural source localization mainly associated with temporal cortex and auditory network activation (Britz et al., 2010; Custo et al., 2017). Microstate B is related to visual processing, self-visualization, autobiographical memory, and scene visualization (Koenig et al., 2002; Britz et al., 2010). In autobiographical memory tasks, its occurrence rate is higher and associated with the "scene reconstruction subsystem" (Bréchet et al., 2019). Its presence duration increases after visual stimulation or in eyes-open states (Tarailis et al., 2024). In unsolved condition, microstate A representing auditory information processing showed longer duration and higher occurrence frequency during initial problem presentation, which we consider may reflect participants' deep processing of word pronunciation and semantic information at the auditory level. In middle and late problem-solving stages, longer mean duration of microstate B may relate to participants' attentional fixation on stimulus material (visual form). Remote association tests require participants to quickly identify and associate based on given words. Therefore, excessive attention to word pronunciation and semantic information and later visual attentional fixation on given words may affect judgment of connections between words, thereby influencing problem solving.

4.2 Neural Processing Patterns in Non-Insight Problem Solving

In both successful problem-solving conditions, microstate D showed relatively longer mean duration and higher occurrence frequency during initial problem presentation stage. This finding aligns with previous research on the important role of executive function in problem solving (Beaty et al., 2015; Lin et al., 2022; Lloyd-Cox et al., 2022), indicating that successful problem solving depends on executive function' s regulation of information processing systems. In middle and late problem-solving stages, microstate D promoted problem solving mainly through transitions with other microstates. This may mean that executive function achieves more effective information processing and promotes problem solving through multiple frequent interactions with other cognitive processes.

During initial problem presentation stage, insight and non-insight solutions showed similar processing patterns, both displaying longer mean duration of microstate A and higher occurrence frequency of microstate B. As the process progressed, non-insight condition showed shortened mean duration of microstate A but increased mean duration of microstate B, and occurrence frequency of microstate B reached highest significance level in response stage ($p<0.001$). Non-insight problem solving is characterized by completing logical analysis based on stimulus material to reach answers. In verbal problems, this manifests as participants' effective activation spreading based on stimulus presentation form (visual). The gradual enhancement of microstate B (representing visual attention and imagination-related cognitive processes) in non-insight problem solving confirms this. Figure 10 intuitively shows that under non-insight condition, microstates B and D have higher participation weights, while microstate C shows no advantage in mean duration, occurrence frequency, or transition probability at any stage. These results may reflect executive function' s active regulation of information processing, while unconscious processing may play a minimal role in non-insight solutions, at least not effectively manifested in microstates. This result aligns with previous research on non-insight problem solving (or analytical problem solving), indicating significant differences in neural processing patterns between insight and non-insight problem solving (Beeman et al., 2004; Yu et al., 2022; Bieth et al., 2024). Notably, although microstate A did not show similar functional role as microstate B, microstate A also played a certain role in non-insight problem solving. Non-insight problem solving in microstate time series showed frequent bidirectional transition patterns among microstates A, B, and D in middle and late problem-solving stages, indicating that although auditory-semantic information processing was not the dominant factor, it had substantial interactions with visual and executive function-related states during the solution process, playing an important participatory role. Previous research also reported significant correlations between microstates A and B (Kleinert et al., 2023), confirming the importance of perceptual information processing and multi-channel conversion in non-insight problem solving. Furthermore, this study' s non-insight problem solving was consistently supported by perceptual information processing and executive function systems, without involving microstate C, supporting the view that non-insight problem solving occurs above the level of consciousness.

4.3 Neural Processing Patterns in Insight Problem Solving

During the problem presentation stage of insight problem solving, both microstates B and D showed significantly higher occurrence frequencies than other microstates, possibly meaning that in early stages participants relied more on visual processing of presented text, with executive function playing significant regulatory role during this period. However, in middle and late stages of insight problem solving, mean duration and occurrence frequency of microstate B continuously and significantly decreased across all three time windows. Meanwhile, mean duration and occurrence frequency of microstate A continuously and significantly increased across all three time windows, possibly reflecting changes in information processing mode during insight problem solving—from primarily relying on visual modality to represent problems in early stages to gradual dominance of modalities related to auditory-semantic information. We interpret this specific change pattern as indicating that after effective initial problem representation, insight problem solving may utilize relatively indirect modalities (or modalities more detached from stimulus material presentation form) to jointly process the problem.

Moreover, neural processing patterns in insight problem solving depend not only on executive function' s regulatory role but also on enhanced activation related to the default mode network throughout the temporal sequence. Specifically, in initial problem presentation stage of insight condition, transitions from microstate C to microstate B significantly increased. In problem solving and response stages, frequent transitions occurred among microstates A, C, and D, and occurrence frequency of microstate C gradually increased across all three time windows. The default mode network is generally considered task-insensitive and more active during brain resting states or situations without explicit task instructions (Dohmatob et al., 2020; Yeshurun et al., 2021). Previous research has reached consensus on the existence of unconscious processing during insight problem solving, but few studies have directly investigated how unconscious processing operates during insight problem solving and whether it is mutually exclusive with other cognitive processes. Our results provide a clear but relatively coarse answer. Microstate C, which is task-unrelated and represents part of the default mode network, showed more significant activity during insight-oriented problem solving, gradually strengthening over time and reaching strongest level in response stage. This result also aligns with previous summaries and reflections on insight problem solving processes (Bilalić et al., 2021; Shen et al., 2018): when conventional approaches fail to solve problems, individuals fall into mental impasses. At this stage, individuals may no longer consciously continue thinking about the problem, shifting from external to internal attention and entering unconscious processing of the problem. However, insight often occurs in an instant, so immediately before problem solving, individuals may be in a very strong unconscious processing state and rapidly switch to conscious processing when the correct answer emerges (Beeman et al., 2004). This result was again confirmed in our time-frequency analysis results, where gamma band enhancement in right temporal region from 0.50s to 0.45s before problem solving may mean that semantic integration promotes sudden conscious availability of solution words. However, it is worth considering that in Beeman et al. (2004), the gamma burst in right temporal region occurred from 0.30s to 0.02s before problem solving, which differs somewhat from our finding of 0.50s to 0.45s before problem solving. We speculate this difference may be caused by using English CRA task with Chinese participants. Although our behavioral results and main neural results indicate L2 processing had minimal impact on this study, subtle differences in L2 processing may manifest as earlier onset and shorter duration of gamma band energy increase. English CRA tasks may have greater semantic distance for Chinese participants, so the right temporal region responsible for difficult semantic processing may need to initiate coarse semantic integration functions earlier to compensate for distant connections (Sun et al., 2015; Yang, 2012). Gamma band energy increase is considered a mechanism supporting such long-range neural connections (Bartoli et al., 2024; Van et al., 2008). Once connections are completed, representations may rapidly enter consciousness, manifesting as earlier and compressed gamma bursts.

Finally, microstate D also supported insight problem solving throughout the process through frequent interactions with other microstates. This echoes previous research in creative domains (including insight problem solving) on executive function and default mode network, indicating that these seemingly antagonistic networks show a collaborative trend in creative tasks, supporting creativity through different mechanisms (Beaty et al., 2015; Shen et al., 2018). However, although previous research using fMRI with ROI-to-ROI analysis revealed coupling patterns between default mode network and executive function network during tasks, such analysis cannot fully capture complex interactions of these networks across different time scales. Therefore, this study explored how brain activities related to creative thinking interact at more sensitive time scales. Through comparison of three solution conditions, we propose that microstate metrics related to default mode network are inseparable from insight problem solving, supporting insight solutions at different stages in various forms (mean duration, occurrence probability, and mutual transitions with other topographies). These results provide insights into the relationship between unconscious processing and insight problem solving, yet unconscious processing alone is insufficient for insight; successful problem solving still requires top-down regulation of information processing by executive function.

4.4 Study Limitations and Future Directions

Our data supported that the most appropriate number of microstate categories was four, and subsequent results and discussion were based on parameters of these four topographies and their potentially associated cognitive meanings. Although results suggest that insight problem solving most clearly involves these four microstates, we cannot exclude whether other microstates and their associated cognitive processes also play important roles in insight problem solving. Future research could further explore this issue under more specific research questions and experimental designs. Additionally, although microstates can provide an overview of how multiple cognitive processes operate in temporal sequences, their greatest significance lies in providing possible directions for subsequent purposeful exploration of neural processing patterns of certain cognitive processes in a task. Future research could combine machine learning or multimodal analysis to verify some indicators already found to play key roles in insight problem solving, thereby further clarifying cognitive meanings represented by multiple microstates and key processes involved in insight problem solving.

Given that this study aimed to describe interaction forms of multiple cognitive processes at different stages of insight problem solving, especially how cognitive processes potentially representing unconscious processing interact with other processes, using Chinese CRA tasks that could trigger richer experiences and associations in participants would not be very appropriate, as it might make cognitive processes more complex and uncontrollable. Moreover, this study' s results are preliminary. English CRA tasks can serve as a "universal" or "neutral" test tool, reducing confounding variables from test material differences and making research conclusions more persuasive. Although recruited and screened Chinese high-English-proficiency participants in this study showed average solution rates and insight solution rates similar to previous results from English native speakers completing English CRA tasks (see Section 3.1), which could be considered evidence that using English CRA tasks with Chinese participants has minimal impact, this approach is only a result of trade-offs. The temporal difference in time-frequency analysis from previous research suggests that language pragmatics differences should be very carefully considered in insight problem solving. When language barriers are minimized, researchers can more purely investigate cognitive mechanisms of creative insight.

This study described how insight problem solving specificity is manifested through dynamic neural response patterns by comparing insight problem solving, non-insight problem solving, and unsolved conditions. Results revealed that insight problem solving involves at least four important cognitive processes. Fully utilizing visual image information and auditory-semantic information to process, retrieve, and extract information is a basic condition for successful problem solving. Unconscious processing mainly appears in middle and late problem-solving stages and plays a crucial role in insight problem solving. Executive function continuously supports information selection and integration in insight problem solving through regulatory forms.

References

Aziz-Zadeh, L., Kaplan, J. T., & Iacoboni, M. (2009). "Aha!" : The neural correlates of verbal insight solutions. *Human Brain Mapping, 30*(3), 908-916.

Bartoli, E., Devara, E., Dang, H. Q., Rabinovich, R., Mathura, R. K., Anand, A., Pascuzzi, B. R., Adkinson, J., Kenett, Y. N., Bijanki, K. R., Sheth, S. A., & Shofty, B. (2024). Default mode network electrophysiological dynamics and causal role in creative thinking. *Brain: a Journal of Neurology, 147*(10), 3409-3425.

Beaty, R. E., Benedek, M., Barry Kaufman, S., & Silvia, P. J. (2015). Default and executive network coupling supports creative idea production. *Scientific Reports, 5*(1), 10964.

Benedek, M., Christensen, A. P., Fink, A., & Beaty, R. E. (2019). Creativity assessment in neuroscience research. *Psychology of Aesthetics, Creativity, and the Arts, 13*(2), 218.

Betzel, R. F., Erickson, M. A., Abell, M., O' Donnell, B. F., Hetrick, W. P., & Sporns, O. (2012). Synchronization dynamics and evidence for a repertoire of network states in resting EEG. *Frontiers in Computational Neuroscience, 6*, 74.

Bieth, T., Ovando-Tellez, M., Lopez-Persem, A., Garcin, B., Hugueville, L., Lehongre, K., ···& Volle, E. (2024). Time course of EEG power during creative problem-solving with insight or remote thinking. *Human Brain Mapping, 45*(1), e26547.

Bilalić, M., Graf, M., Vaci, N., & Danek, A. H. (2021). The temporal dynamics of insight problem solving–restructuring might not always be sudden. *Thinking & Reasoning, 27*(1), 1-37.

Bowden, E. M., & Jung-Beeman, M. (2003). Normative data for 144 compound remote associate problems. *Behavior Research Methods, Instruments, & Computers, 35*, 634-639.

Bréchet, L., Brunet, D., Birot, G., Gruetter, R., Michel, C. M., & Jorge, J. (2019). Capturing the spatiotemporal dynamics of self-generated, task-initiated thoughts with EEG and fMRI. *Neuroimage, 194*, 82-92.

Britz, J., Van De Ville, D., & Michel, C. M. (2010). BOLD correlates of EEG topography reveal rapid resting-state network dynamics. *Neuroimage, 52*(4), 1162-1170.

Brouwer, H., & Hoeks, J. C. (2013). A time and place for language comprehension: mapping the N400 and the P600 to a minimal cortical network. *Frontiers in Human Neuroscience, 7*, 758.

Croce, P., Zappasodi, F., Spadone, S., & Capotosto, P. (2018). Magnetic stimulation selectively affects pre-stimulus EEG microstates. *NeuroImage, 176*, 239–245.

Custo, A., Van De Ville, D., Wells, W. M., Tomescu, M. I., Brunet, D., & Michel, C. M. (2017). Electroencephalographic resting-state networks: source localization of microstates. *Brain Connectivity, 7*(10), 671–682.

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, 134*(1), 9–21.

Dijksterhuis, A., & Nordgren, L. F. (2006). A theory of unconscious thought. *Perspectives on Psychological Science: a Journal of the Association for Psychological Science, 1*(2), 95–109.

Dohmatob, E., Dumas, G., & Bzdok, D. (2020). Dark control: The default mode network as a reinforcement learning agent. *Human Brain Mapping, 41*(12), 3318–3341.

Erickson, B., Truelove-Hill, M., Oh, Y., Anderson, J., Zhang, F. Z., & Kounios, J. (2018). Resting-state brain oscillations predict trait-like cognitive styles. *Neuropsychologia, 120*, 1–8.

Fink, A., Graif, B., & Neubauer, A. C. (2009). Brain correlates underlying creative thinking: EEG alpha activity in professional vs. novice dancers. *NeuroImage, 46*(3), 854–862.

Fleck, J. I., & Kounios, J. (2009). Intuition, creativity, and unconscious aspects of problem solving. In *Encyclopedia of Consciousness* (pp. 431–446). Elsevier.

Gao, Y., & Zhang, H. (2014). Unconscious processing modulates creative problem solving: Evidence from an electrophysiological study. *Consciousness and Cognition, 26*, 64–73.

Gilhooly K. J. (2016). Incubation and intuition in creative problem solving. *Frontiers in Psychology, 7*, 1076.

Haavold, P. Ø., & Sriraman, B. (2022). Creativity in problem solving: integrating two different views of insight. *ZDM–Mathematics Education, 54*(1), 83–96.

Hill, A. T., Bailey, N. W., Zomorrodi, R., Hadas, I., Kirkovski, M., Das, S., Lum, J. A. G., & Enticott, P. G. (2023). EEG microstates in early-to-middle childhood show associations with age, biological sex, and alpha power. *Human Brain Mapping, 44*(18), 6484–6498.

Huang, F., Zhao, Q., Zhou, Z., & Luo, J. (2019). People got lost in solving a set of similar problems. *NeuroImage, 186*, 192–199.

Jung-Beeman, M., Bowden, E. M., Haberman, J., Frymiare, J. L., Arambel-Liu, S., Greenblatt, R., ···& Kounios, J. (2004). Neural activity when people solve verbal problems with insight. *PLoS Biology, 2*(4), e97.

Khanna, A., Pascual-Leone, A., Michel, C. M., & Farzan, F. (2015). Microstates in resting-state EEG: current status and future directions. *Neuroscience & Biobehavioral Reviews, 49*, 105–113.

Koenig, T., Prichep, L., Lehmann, D., Sosa, P. V., Braeker, E., Kleinlogel, H., ···& John, E. R. (2002). Millisecond by millisecond, year by year: normative EEG microstates and developmental stages. *Neuroimage, 16*(1), 41–48.

Kohler, W. (1985). *The mentality of apes.* Routledge.

Lehmann, D., Ozaki, H., & Pál, I. (1987). EEG alpha map series: brain microstates by space-oriented adaptive segmentation. *Electroencephalography and clinical neurophysiology, 67*(3), 271–288.

Lehmann, D., Pascual-Marqui, R. D., & Michel, C. M. (2009). EEG microstates. *Scholarpedia, 4*(3), 7632.

Leszczynski, M., Chaieb, L., Reber, T. P., Derner, M., Axmacher, N., & Fell, J. (2017). Mind wandering simultaneously prolongs reactions and promotes creative incubation. *Scientific Reports, 7*(1), 10197.

Lin, J., Chen, Y., Xie J., & Mo, L. (2022). Altered brain connectivity patterns of individual differences in insightful problem solving. *Frontiers in Behavioral Neuroscience, 16*, 905806.

Liu, C., Tu, S., Guan, J., Zhou, Z., Ma, J., & Shi, Z. (2024). How does unconscious processing promote creative problem-solving? An examination using priming methods. *Thinking & Reasoning, 31*(3), 374–397.

Liu, D., Hao, L., Han, L., Zhou, Y., Qin, S., Niki, K., Shen, W., Shi, B., & Luo, J. (2023). The optimal balance of controlled and spontaneous processing in insight problem solving: fMRI evidence from Chinese idiom guessing. *Psychophysiology, 60*(7), e14240.

Liu, Y., Nour, M. M., Schuck, N. W., Behrens, T. E. J., & Dolan, R. J. (2022). Decoding cognition from spontaneous neural activity. *Nature Reviews Neuroscience, 23*(4), 204–214.

Lloyd-Cox, J., Chen, Q., & Beaty, R. E. (2022). The time course of creativity: Multivariate classification of default and executive network contributions to creative cognition over time. *Cortex, 156*, 90–105.

Lopez, K. L., Monachino, A. D., Morales, S., Leach, S. C., Bowers, M. E., & Gabard-Durnam, L. J. (2022). HAPPILEE: HAPPE In Low Electrode Electroencephalography, a standardized pre-processing software for lower density recordings. *NeuroImage, 260*, 119390.

Lu, Y., & Singer, W. (2023). Dynamic signatures of the Eureka effect: an EEG study. *Cerebral Cortex, 33*(13), 8670–8684.

Luo, J. (2004). Neural correlates of insight. *Acta Psychologica Sinica, 36*(2), 219-234.

Mai, X. Q., Luo, J., Wu, J. H., & Luo, Y. J. (2004). "Aha!" effects in a guessing riddle task: An ERP study. *Human Brain Mapping, 23*(2), 128-128.

Michel, C. M., Bréchet, L., Schiller, B., & Koenig, T. (2024). Current state of EEG/ERP microstate research. *Brain Topography, 37*(2), 169-180.

Musso, F., Brinkmeyer, J., Mobascher, A., Warbrick, T., & Winterer, G. (2010). Spontaneous brain activity and EEG microstates. A novel EEG/fMRI analysis approach to explore resting-state networks. *Neuroimage, 52*(4), 1149-1161.

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience, 2011*, 156869.

Pan, D. N., Hoid, D., Gu, R. L., & Li, X. (2020). Emotional working memory training reduces rumination and alters the EEG microstate in anxious individuals. *NeuroImage: Clinical, 28*, 102488.

Pan, M. W., Song, J. Q., & Deng, H. (2019). Development and validation of self-rating scales in online English writing diagnostic tests. *Frontiers of Foreign Language Education Research, 2*(4), 33-41.

Poulsen, A. T., Pedroni, A., Langer, N., & Hansen, L. K. (2018). Microstate EEGlab toolbox: An introductory guide. *BioRxiv, 289850*.

Qiu, J., Li, H., Jou, J., Liu, J., Luo, Y., Feng, T., …& Zhang, Q. (2010). Neural correlates of the "Aha" experiences: evidence from an fMRI study of insight problem solving. *Cortex, 46*(3), 397-403.

Rominger, C., Papousek, I., Perchtold, C. M., Weber, B., Weiss, E. M., & Fink, A. (2018). The creative brain in the figural domain: Distinct patterns of EEG alpha power during idea generation and idea elaboration. *Neuropsychologia, 118*, 13-19.

Satpute, A. B., & Lindquist, K. A. (2019). The Default Mode Network' s Role in Discrete Emotion. *Trends in Cognitive Sciences, 23*(10), 851-864.

Schiller, B., Gianotti, L. R., Baumgartner, T., Nash, K., Koenig, T., & Knoch, D. (2016). Clocking the social mind by identifying mental processes in the IAT with electrical neuroimaging. *Proceedings of the National Academy of Sciences, 113*(10), 2786-2791.

Shen, W. B., Liu, C., Luo, J., & Yu, J. (2012). Brain perceived intuitively mental impasses in insight problem solving: An ERP study. *Acta Psychologica Sinica, 44*(7), 924-935.

Shen, W., Tong, Y., Li, F., Yuan, Y., Hommel, B., Liu, C., & Luo, J. (2018). Tracking the neurodynamics of insight: A meta-analysis of neuroimaging studies. *Biological Psychology, 138*, 189-198.

Sun, Y., Cai, Y., & Lu, S. (2015). Hemispheric asymmetry in the influence of language on visual perception. *Consciousness and Cognition, 34*, 16–27.

Tan, T., Zou, H., Chen, C., & Luo, J. (2015). Mind wandering and the incubation effect in insight problem solving. *Creativity Research Journal, 27*(4), 375–382.

Tarailis, P., Koenig, T., Michel, C. M., & Griškova-Bulanova, I. (2024). The functional aspects of resting EEG microstates: A systematic review. *Brain Topography, 37*(2), 181–217.

Van Der Werf, J., Jensen, O., Fries, P., & Medendorp, W. P. (2008). Gamma-band activity in human posterior parietal cortex encodes the motor goal during delayed prosaccades and antisaccades. *The Journal of Neuroscience, 28*(34), 8397–8405.

Wang, H., Guo, Y., Tu, Y., Peng, W., Lu, X., Bi, Y., Iannetti, G. D., & Hu, L. (2023). Neural processes responsible for the translation of sustained nociceptive inputs into subjective pain experience. *Cerebral Cortex, 33*(3), 1023–1038.

Wang, T., Zhang, Q., Li, H., Qiu, J., Tu, S., & Yu, C. (2009). The time course of Chinese riddles solving: Evidence from an ERP study. *Behavioural Brain Research, 199*(2), 278–282.

Yang, J. (2012). The role of the right hemisphere in metaphor comprehension: A meta-analysis of functional magnetic resonance imaging studies. *Human Brain Mapping, 35*(1), 107–122.

Yeshurun, Y., Nguyen, M., & Hasson, U. (2021). The default mode network: where the idiosyncratic self meets the shared social world. *Nature reviews neuroscience, 22*(3), 181–192.

Yu, Y., Oh, Y., Kounios, J., & Beeman, M. (2022). Dynamics of hidden brain states when people solve verbal puzzles. *NeuroImage, 255*, 119202.

Yue, L., Iannetti, G. D., & Hu, L. (2020). The neural origin of nociceptive-Induced gamma-band oscillations. *The Journal of neuroscience: The Official Journal of the Society for Neuroscience, 40*(17), 3478–3490.

Zanesco, A. P., Denkova, E., & Jha, A. P. (2021). Self-reported mind wandering and response time variability differentiate prestimulus electroencephalogram microstate dynamics during a sustained attention task. *Journal of Cognitive Neuroscience, 33*(1), 28–45.

Zhao, Q., Li, S., Chen, S., Zhou, Z., & Cheng, L. (2015). Dynamic neural processing mode of creative problem solving. *Advances in Psychological Science, 23*(3), 375–384.

Zhao, Q., Wei, L., Li, Y., Zhou, Z., Zhao, L., & Tang, L. (2017). Right hemispheric dominance in forming novel semantic associations. *Acta Psychologica Sinica, 49*(11), 1370–1382.

Zhou, S., Chen, S., Wang, S., Zhao, Q., Zhou, Z., & Lu, C. (2018). Temporal and spatial patterns of neural activity associated with information selection in open-ended creativity. *Neuroscience, 371*, 268-276.

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