Effects of Model Merge on Developers' Brain Dynamics: An EEG Microstate Analysis

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***Abstract*—Model merging in model-based engineering imposes high cognitive demands, as developers must identify, reconcile, and integrate changes across parallel artifacts. To explore the neural dynamics of this process, we conducted a controlled experiment with 35 developers performing merge tasks in two representational formats—sentential (Java code) and diagrammatic (UML class diagrams)—while EEG was continuously recorded. We clustered EEG signals into the four canonical microstate classes (A–D), which are well-established in cognitive neuroscience and represent recurring large-scale brain activity patterns. In alternating cycles of eyes-closed rest and task execution, we analyzed microstate dynamics and found diametrically opposite patterns depending on representation: in the sentential format, microstates A, C, and D increased significantly in duration, occurrence, and coverage, whereas in the diagrammatic format, A and C decreased, B declined moderately, and D showed reductions in occurrence and coverage. These findings reinforce the feasibility of microstate metrics as fine-grained biomarkers of cognitive overload in model-integration operations, paving the way for cognitively aware tools and adaptive environments capable of automatically adjusting abstraction levels or issuing high-load alerts.**

***Index Terms*—software merge, cognitive task, EEG Microstate.**

I. Introduction

The rapid evolution of technology and the omnipresence of software in modern society underscore the critical importance of maintaining high-quality software products and services [1]. However, in large-scale projects, this quality depends on a fundamentally challenging process: merging parallel contributions.

In collaborative environments, developers often work in parallel on different modules—ranging from planning and design to coding, testing, and maintenance—which generates multiple versions of the same artifact [2]. The merge operation integrates two or more parallel versions A_a (base) and A_b (target) into a single unified artifact A_{ab}, involving not only identification of edits in each input but also detection and resolution of conflicts arising from simultaneous modifications [3], [4]. These conflicts—from trivial overlaps to deep structural contradictions—make merging a critical, error-prone, and cognitively demanding task.

From the developer's perspective, merging artifacts requires the coordinated deployment of mental processes: focused attention to spot discrepancies, working memory to understand incremental changes, and executive reasoning to decide and apply conflict-resolution strategies [5], [6]. Moreover, the abstraction level of the artifact plays a decisive role. Sentential artifacts (Java source code) present detailed, sequential information that can overload working memory. In contrast, diagrammatic artifacts (UML diagrams) preserve spatial and structural relationships, leveraging visual reasoning and reducing cognitive load by omitting non-essential details [6]–[8].

To capture rapid transitions among these cognitive processes during merging, we employed EEG microstate analysis — a technique that segments ongoing cortical activity into quasi-stable topographies lasting 80–120ms and quantifies parameters such as duration, occurrence, coverage, and transition probabilities [9]–[11]. Although widely applied in neuropsychiatric research (schizophrenia, dementia, narcolepsy, etc.), its use in software-engineering tasks remained unexplored [12].

For this reason, we conducted a controlled experiment with 35 developers who performed ten merge tasks—five in sentential format and five in diagrammatic format—while we continuously recorded their EEG. Alternating 30s eyes-closed resting baselines with unconstrained merge problems, we extracted segments for microstate analysis.

Our results revealed format-specific modulations: in sentential merges, microstates A, C, and D showed significant increases in duration, occurrence, and coverage—indicating greater recruitment of working-memory and attention networks—whereas in diagrammatic merges, those same states displayed marked reductions, with microstate B undergoing only minor adjustments. These inverse patterns validate EEG microstate as real-time biomarkers of the distinct cognitive demands imposed by different levels of abstraction.

Thus, this work represents an initial contribution to the application of EEG microstate analysis in software-merge scenarios [12], while also laying the groundwork for adaptive development environments that monitor cognitive load and provide contextual support, ultimately optimizing quality and efficiency in collaborative software engineering.

II. Background and Motivating example

A. Motivating example in Software Merge

In modern software development, parallel workflows are supported by version-control systems (VCS) that enable multiple developers to work concurrently on isolated branches. While branching improves productivity, reintegrating these branches into the main line often triggers merge conflicts when a VCS cannot automatically reconcile independent edits to the same artifact [14], [15]. Such conflicts range from trivial overlaps to complex, time-consuming issues, especially as commits accumulate across branches before final delivery merges [16]. Effective merge strategies and tooling are, therefore, essential to maintain artifact integrity throughout collaborative development.

The merge process refers to combining two or more versions of an artifact created in parallel [3]. As a process, it involves a series of tasks to combine two input artifacts, A_a and A_b, into a single output artifact A_{ab}. These tasks include identifying the changes made to each input artifact, resolving conflicts that may have arisen due to simultaneous modifications, and creating an integrated version incorporating the changes from both input artifacts.

A_a and A_b denote, respectively, the base and the target of a merge relationship. A_b contains a set of increments that must be applied to A_a in order to produce A_{ab}. After incorporating these updates, equivalent elements in A_a and A_b are aligned and combined according to a chosen merge strategy. A_a and A_b often contain conflicting changes, and these conflicts are frequently resolved incorrectly, leading to inconsistencies in the merged output artefact; consequently, model merging remains a highly error-prone task [13].

In this study, we leverage a canonical software merge scenario merging a base artefact A_a and a target artefact A_b into the desired artefact A_{ab} to probe how representational format shapes brain dynamics.

Figure 1a shows the diagrammatic version (UML class diagrams), in which the concrete class `Researcher` (A_a) must become abstract and inherit a new `name:String` and `salary:double` from A_b, while adding a `Professor` subclass. Figure 1b renders the identical conflict in sentential form (Java source code).

Although the logical operations—aligning equivalent elements, reconciling `isAbstract`, attribute types and visibilities are the same, diagrammatic merges engage visuospatial pattern recognition. In contrast, sentential merges demand detailed, sequential parsing of code.

B. Levels of Representation in Software Merge Tasks

Abstraction underpins all software-merge tasks by determining the level of detail developers must hold in mind when reconciling two artifacts into a merged artifact [17]. In our context, external representations fall into two complementary types [8]: *Sentential representations*: namely, source code in Java, which presents the program as a linear sequence of tokens and statements. Although immediately legible, they convey relationships (e.g., control flow, inheritance) implicitly, demanding developers to maintain these links in working memory. *Diagrammatic representations*: specifically UML class diagrams, spatially organized classes, attributes, and associations. By preserving topology and geometry, diagrams exploit perceptual "off-loading," letting designers grasp structural patterns at a glance and thereby reducing cognitive load [18].

According to Wagner and Deissenboeck's view of abstraction as context-dependent omission of irrelevant details [19], UML diagrams operate at a higher level of abstraction than code, which remains more concrete.

In merge scenarios, this difference is crucial. When merging UML diagrams, you can rely on visual grouping - glancing at clusters of classes and their `isAbstract` flags - to spot conflicts almost instantly. By contrast, merging the equivalent in source code forces you to read through class declarations, attributes, and method signatures one by one. Cognitive-load theory tells us that once a task exceeds about seven items in working memory, comprehension suffers [6]. Consequently, diagrammatic merges should place far less strain on memory than purely sentential (code-based) merges.

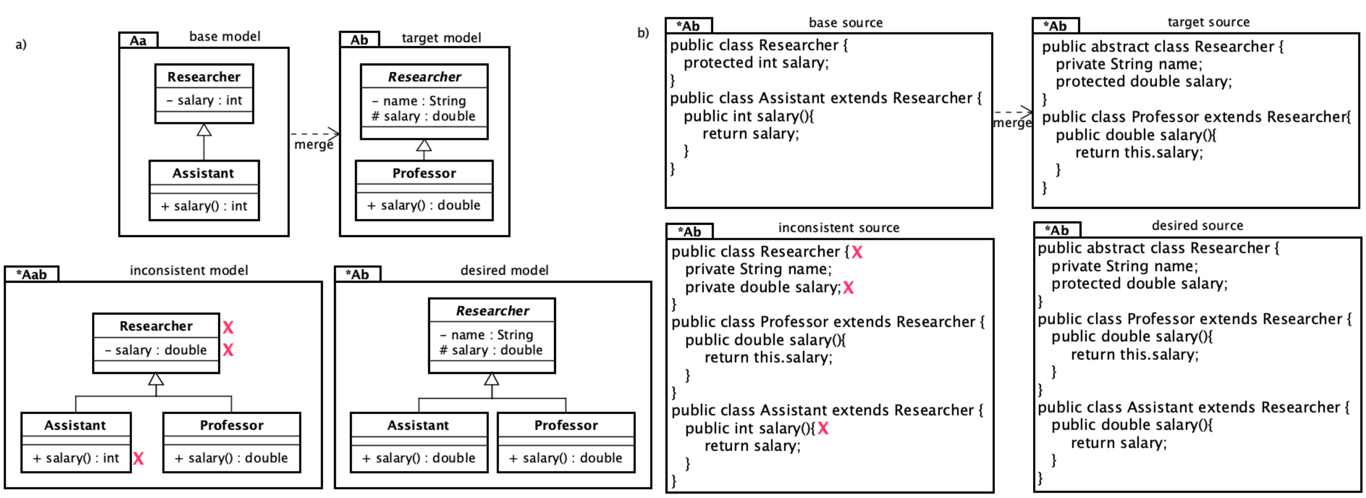

Fig. 1. Illustrative example of model merging in two representational formats: diagrammatic and sentential (adapted from [13])

C. Cognitive Tasks

Cognition is the set of processes by which we perceive, attend to, remember, reason about, and manipulate information such as source code or UML diagrams—relies heavily on working memory and long-term memory structures for programming knowledge [5]. In tasks such as requirements analysis, design, or testing, these capacities are already taxed [20]. Artifact merging exemplifies one of the most cognitively demanding activities in software engineering, since it requires developers to hold multiple representations in mind, detect and resolve conflicts, and reconstruct a coherent unified model.

During the conflict detection phase, developers must carefully scan both input artifacts (whether the concrete vs. abstract Researcher in UML or its Java-code analog) to spot discrepancies in class properties, method signatures, and visibilities. This step engages focused attention and the continuous updating of short-term memory [6], [21]. Next, the understanding-and-modification phase demands logical reasoning as one interprets the intent behind each change (e.g., "Should Researcher be abstract?") and mentally simulates the effects of adopting one value over another. Finally, conflict resolution imposes the most significant burden: it requires weighing business logic constraints against structural integrity, selecting and ordering merge strategies, and thereby exercising complex decision-making under cognitive strain.

To uncover the neural correlates of these microstate dynamics, task-state EEG microstate analysis promises to reveal rapid transitions between large-scale brain networks known to subserve attention [22], [23], memory maintenance [24], [25], and problem-solving [26]. By comparing the same merge problem presented in diagrammatic (UML) versus sentential (Java code) form, we can isolate how the representation format modulates the brain's moment-to-moment configuration of microstates during each of these cognitively intensive merge phases.

D. EEG Microstates Analisys

Assessment of cognitive state has a long history across many domains [1], and in software engineering, this work has progressed from wearable sensors (ECG, EDA, eye-tracking) [27], [28] to invasive imaging (fMRI, fNIRS) [29], [30]. Yet human cognition emerges from rapid, dynamic interactions among distributed neural networks rather than isolated loci [31], [32]. Because fMRI's slow hemodynamics cannot resolve the sub-second processes required to detect, understand and resolve merge conflicts, EEG—with its millisecond precision—offers a window into the temporal unfolding of these operations.

The analysis focused on the four canonical microstate classes (A–D), which have been consistently reported in EEG research [**?**]. Briefly, microstate A is typically associated with occipital visual processing, microstate B with auditory and language-related networks, microstate C with attention and saliency processing, and microstate D with cognitive control and default mode activity [33]. While these functional associations are still subject to ongoing debate, they provide an intuitive mapping between EEG dynamics and large-scale cognitive processes. For our purposes, we use the canonical labeling (A–D) to ensure comparability with prior neuroscience literature.

Most resting-state EEG studies reveal four topographic microstate classes, accounting for 70–80% of the variation [34]. These four EEG microstate classes are referred to as canonical in the literature. Figure 2 shows the three main steps of Microstate EEG analysis, including (a) clustering process, (b) backfitting, and (c) statistical calculation.

EEG microstate analysis segments ongoing cortical activity into quasi-stable topographies (80–120 ms) that reflect transient network configurations [9], [10]. By clustering GFP peaks, back-fitting labels, and extracting parameters (duration, occurrence, coverage, and transitions) (Figure 2) [11], [35], microstate analysis can map how attention, working memory, and reasoning resources are deployed during each merge

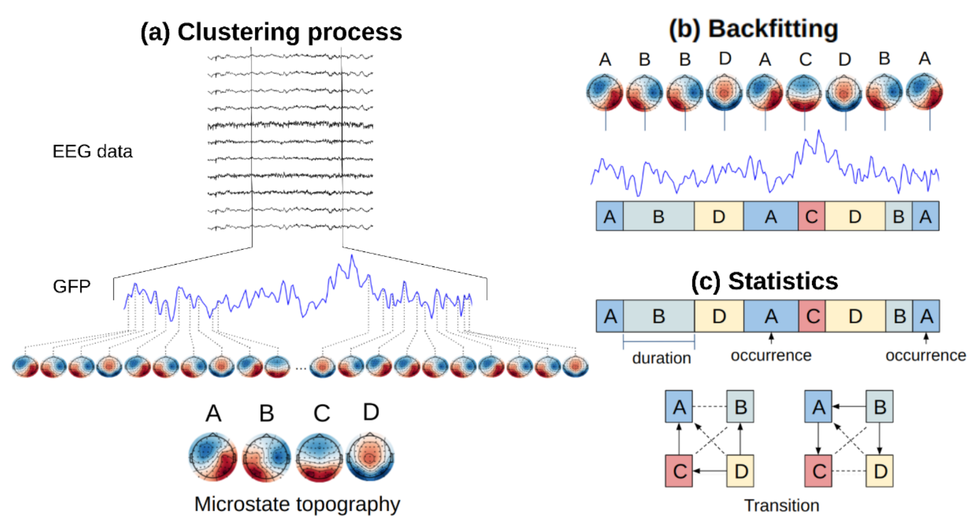

Fig. 2. Representation of the EEG microstate analysis procedures [12]

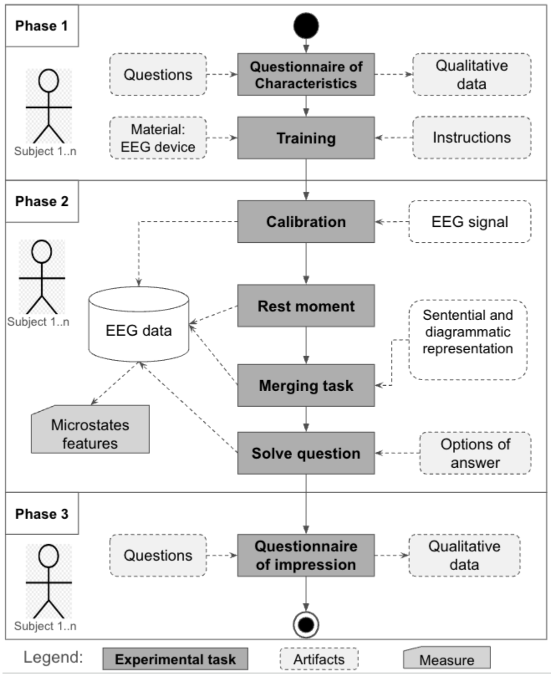

Fig. 3. Proposed experimental process

phase.

In our merge scenario—alternating diagrammatic or sentential merges—the conflict detection phase should manifest as increased occurrence of attention-related microstates; the modification-understanding phase as prolonged durations reflecting working-memory engagement; and the conflict-resolution phase as shifts in coverage and transition probabilities corresponding to decision-making dynamics [6], [21]. Thus, combining cognitive-task theory with EEG microstates enables us to trace the neural signatures of complex merge operations in real-time, revealing how representation format modulates the brain's large-scale state dynamics.

III. Study Design

To design an experiment, we implemented a well-defined process divided into three main phases, each with specific activities. The goal was to minimize interference between the stages and ensure that participants were familiar with the experiment. The subjects individually performed all activities to ensure that no threat was posed to the experimental process. Figure 3 shows how the three phases were organized through an experimental process.

First, participants completed a demographic and background questionnaire and then received hands-on training on both code- and diagram-based merge tasks. They also signed informed consent and image-release forms. In the next phase, the EEG headset and eye tracker were fitted and calibrated to verify signal quality. EEG data were collected continuously in alternating rest–task cycles, comprising ten merge problems (five with sentential artifacts—source code—and five with diagrammatic artifacts—UML diagrams) presented in random order.

Before each task, participants underwent a 30-second eyes-closed resting baseline, a common practice in EEG studies that minimizes visual stimulation and facilitates a relaxed state associated with stable alpha activity [36]. Participants were instructed to sit quietly, relax, and keep their eyes closed during this period to ensure a neutral mental state. EEG was then recorded throughout the entire merge task (with no time limit) as they solved the corresponding multiple-choice problem. After completing all ten tasks, each subject completed an impressions questionnaire, providing subjective feedback to inform future protocol refinements.

Importantly, the paired artifacts in each scenario were matched for structural complexity (identical numbers of classes, methods, attributes, and associations) so that any performance differences could be attributed to representation format rather than task size. To isolate the merging process, all model elements were displayed at once on a single, vertically oriented screen, with no scrolling or file navigation. Complexity increased systematically across the five problems in each group.

The entire study was conducted in a rigorously controlled laboratory environment, equipped with acoustic isolation, regulated lighting, and the removal of non-essential electronics to minimize distractions. Sessions lasted approximately 50 minutes (about 32 minutes of active tasks), during which participants used five key devices (Figure 4): the Emotiv EPOC+ headset (14-channel EEG at 256 Hz plus three gyroscopes, via Bluetooth 4.0), its wireless receiver connected to a laptop, a 19' Dell E1909W monitor (1440×900 px, 75 Hz), a wired QWERTY keyboard, and a Tobii Tracker 5 eye-tracker. Although eye-tracking data were recorded for future work, the present analysis focuses exclusively on EEG microstate dynamics.

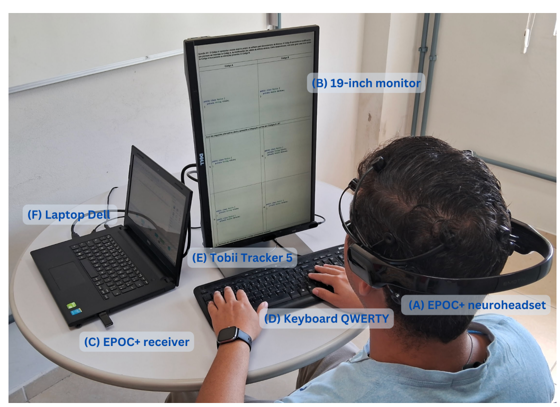

Fig. 4. Participant in the experimental setup

A. Selection of Participants

Thirty-five volunteer practitioners—developers, analysts, architects, and project managers—were recruited via email and personal contacts to ensure a mix of theoretical knowledge and hands-on experience in software development. All participants held a sufficient background in object-oriented programming and UML modeling, as verified by a pre-experiment survey using Likert scales to assess their Java and OO skills. Before beginning, they received complete information on the study's goals and risks, provided written informed consent, and participated in accordance with a protocol approved by the institution's Ethics Committee.

B. Experimental Tasks

The experiment consists of 10 tasks divided into two groups: sentential and diagrammatic representations. The task is to indicate which alternatives present the correct integration of input artifacts A and B. Five possible answers (1–5) are offered, each corresponding to a different integrated model alternative for each multiple-choice question. To maintain focus on the merge itself, all elements were displayed simultaneously on a single vertically oriented monitor—no scrolling or file navigation was required. Task difficulty ramped up across the five problems, each varying in the number of classes, methods, and iterations.

C. Dependent Variable: EEG Microstate Analysis

EEG microstate analysis quantifies the temporal dynamics of large-scale cortical networks through standard parameters: *duration* (mean stability time), *occurrence* (frequency of dominance), *coverage* (proportion of total recording time), and *global field power (GFP)* (signal strength at peaks). These features served as our dependent variable, allowing comparison of microstate dynamics between sentential and diagrammatic merge tasks.

D. Validity Threats

This study faces threats to validity. The merge tasks were simplified for a lab setting, which may reduce ecological validity, and their selection was not fully transparent, potentially biasing toward diagrammatic cases. Moreover, although EEG microstates are established correlates of cognition, their use as direct indicators of cognitive load in software engineering remains uncertain. Finally, the lack of explicit performance measures (e.g., correctness, completion time) constrains internal validity, making it harder to separate task difficulty from EEG effects.

IV. Emerging Results

Figure 5 presents the normalized EEG microstate topographies, revealing four reproducible classes. Following the nomenclature of Koenig et al. [37], [38], the two maps with predominant unilateral frontal focus are designated type A and B, the map exhibiting an anterior–posterior gradient is designated type C, and the pattern centered over the occipital cortex is designated type D. We then examined these templates across our four experimental conditions diagrammatic rest (DR), sentential rest (SR), diagrammatic task (DT), and sentential task (ST) to characterize how each condition modulates microstate dynamics.

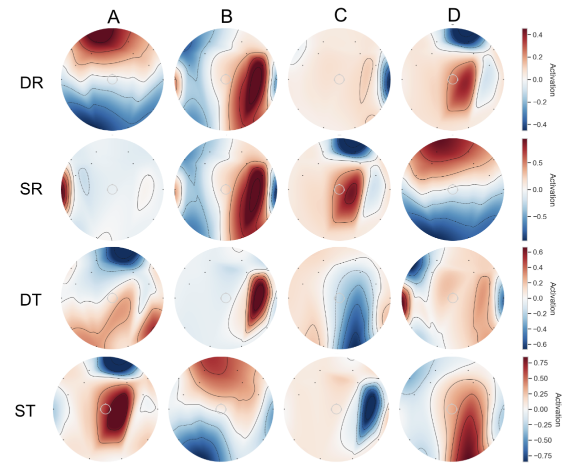

Fig. 5. Four microstates of EEG recordings

The results show clear differences in microstate dynamics between rest and task conditions. Table I summarizes the key contrasts between Sentential Rest and Sentential Task (SR × ST), and between Diagrammatic Rest and Diagrammatic Task (DR × DT), across microstates A–D and the four primary EEG features. Statistical analyses were conducted using the Mann–Whitney test. Asterisks (*) indicate significance at ($p < 0.05$) after Bonferroni correction; values in bold indicate strong significance ($p < 0.001*$). EEG preprocessing and analyses were performed with MNE [39] and Pycrostates [40].

Transition to task strongly alters microstate profiles in a processing-dependent manner. In the sentential axis (SR vs ST) we observed: in type A, duration, occurrence and coverage all increased significantly ($p < 0.001$); type B showed only a modest increase in duration ($p = 0.020$) with no change in occurrence or coverage; type C exhibited robust increases across all three parameters ($p < 0.001$); and type D demonstrated a decrease in duration ($p < 0.001$) accompanied by reductions in occurrence and coverage ($p < 0.001$). By contrast, **diagrammatic tasks induce the opposite pattern, attenuating microstate engagement**. In the diagrammatic axis (DR vs DT), type A showed decreases in duration ($p < 0.001$), occurrence ($p < 0.001$), and coverage ($p < 0.001$); type B exhibited a slight decline in duration ($p = 0.026$) without significant changes in other metrics; type C had decreases in both duration and coverage ($p < 0.001$); and type D remained stable in duration ($p = 1.000$) but declined in occurrence and coverage ($p < 0.001$). The Figure 6 immediately shows that, in sentential tasks, microstates A and C strongly increase in duration and coverage (red), while B and D change little or even decrease. Conversely, in diagrammatic tasks (DT–DR), microstate A shows pronounced decreases in duration and occurrence (negative values/blue), whereas microstate C shows increases across duration, occurrence, and coverage (positive values/red). B and D vary more moderately.

Global field potential (GFP) changes mirror microstate-axis effects. The mean global field potential (GFP) followed analogous patterns: along the sentential axis, GFP decreased

TABLE I
SR SENTENTIAL MERGE IN THE RESTING STATE, DT DIAGRAMMATIC MERGE IN TASK STATE, DR DIAGRAMMATIC MERGE IN RESTING STATE, ST SENTENTIAL MERGE IN TASK STATE, GFP GLOBAL FIELD POTENTIAL, MEAN (±STANDARD DEVIATION).

		Mean (±SD)				SR vs ST		DR vs DT	
Feature	Type	SR	ST	DR	DT	u	p	u	p
Duration (ms)	A	63.9 (±45.0)	108.6 (±72.1)	233.3 (±149.8)	155.3 (±102.1)	5794.0	**< 0.001∗**	17202.0	**< 0.001∗**
	B	152.7 (±171.5)	169.8 (±103.7)	142.2 (±83.4)	130.4 (±128.3)	9372.0	**0.020***	14594.0	**0.026***
	C	73.5 (±153.9)	135.1 (±133.6)	62.3 (±51.6)	115.2 (±136.3)	5016.0	**< 0.001∗**	5108.5	**< 0.001∗**
	D	250.9 (±226.8)	122.8 (±85.7)	81.7 (±147.5)	126.7 (±46.4)	19863.0	**< 0.001∗**	4783.5	**< 0.001∗**
Occurrence (Hz)	A	0.5 (±0.6)	0.9 (±0.9)	2.6 (±0.7)	2.2 (±0.9)	8345.0	**< 0.001∗**	14360.0	**0.070***
	B	2.4 (±0.8)	2.4 (±0.8)	2.4 (±0.8)	1.2 (±0.9)	11657.0	**1.000***	19953.0	**< 0.001∗**
	C	0.4 (±0.6)	1.4 (±0.9)	0.3 (±0.4)	1.1 (±0.9)	3846.0	**< 0.001∗**	3999.0	**< 0.001∗**
	D	2.5 (±0.7)	1.9 (±0.9)	0.5 (±0.7)	2.1 (±0.9)	16834.0	**< 0.001∗**	2078.0	**< 0.001∗**
Coverage (%)	A	4.6 (±7.8)	12.0 (±16.7)	54.9 (±21.1)	35.7 (±22.2)	7568.0	**< 0.001∗**	17723.0	**< 0.001∗**
	B	35.5 (±20.7)	41.5 (±21.6)	35.1 (±20.2)	19.9 (±21.8)	9947.0	**0.213***	17774.0	**< 0.001∗**
	C	5.5 (±12.7)	21.5 (±20.8)	3.1 (±7.4)	14.9 (±18.5)	4155.0	**< 0.001∗**	4012.0	**< 0.001∗**
	D	54.4 (±21.9)	25.0 (±19.4)	6.9 (±13.0)	29.5 (±18.2)	20184.0	**< 0.001∗**	2784.0	**< 0.001∗**
GFP (uV)	A	8.8 (±5.9)	10.0 (±6.7)	8.5 (±3.6)	8.0 (±6.7)	8025.0	**1.000***	15568.0	**< 0.001∗**
	B	8.5 (±4.1)	7.3 (±4.0)	9.1 (±5.1)	8.3 (±4.7)	15234.0	**0.001***	13125.0	**0.396***
	C	9.0 (±7.0)	8.3 (±4.2)	8.1 (±5.5)	6.7 (±3.3)	7868.0	**1.000***	11544.0	**0.208***
	D	8.1 (±2.8)	7.2 (±3.4)	9.6 (±8.8)	7.5 (±3.7)	15675.0	**< 0.001∗**	10098.0	**0.779***

in types B and D ($p < 0.001$); along the diagrammatic axis, it fell in type A ($p < 0.001$) and remained non-significant in type C ($p = 0.208$). Mean spatial correlation also declined significantly in several states—especially in the diagrammatic axis (types A–C; $p < 0.001$)—suggesting distinct spatial reorganization.

Elevated microstate metrics during sentential tasks index increased cognitive load. The marked increases in microstate duration, occurrence and coverage observed during sentential tasks can be interpreted as neurophysiological markers of elevated cognitive load. Empirical studies have shown that when working memory or linguistic demands rise, microstate parameters change systematically. For example, Khanna et al. [41] reported that microstate durations lengthen in proportion to memory load, while Michel and Koenig's review [10] highlights that increased coverage of particular microstate classes reflects sustained engagement of large-scale cortical networks under high cognitive demand. Similarly, Britz et al. [42] demonstrated that the probability of occurrence of specific microstates scales with task complexity. In our sentential condition, the robust elevations in types A and C (all $p < 0.001$) thus likely index the additional processing and integration resources recruited by complex sentence comprehension, consistent with the notion that microstate metrics serve as real-time markers of mental workload.

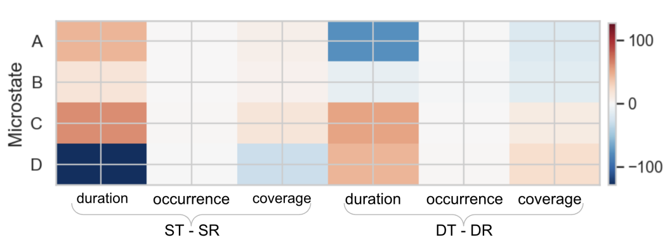

Fig. 6. Heatmap of mean differences (Task vs Rest)

V. Conclusion and Future Plans

The objective of this study was to investigate how EEG microstate dynamics manifest during software merge tasks presented in two representational formats—sentential (Java source code) and diagrammatic (UML class diagrams). To this end, we conducted a controlled experiment in which 35 developers completed merge problems while their EEG was continuously recorded. In alternating cycles of eyes-closed rest and merge-task execution, we extracted both resting and task segments for microstate analysis.

Our findings revealed a diametrically opposite pattern along the two cognitive axes: as participants transitioned from rest to task, microstate parameters changed in opposite directions depending on representation. In the sentential axis (SR vs ST), microstates A, C, and D exhibited highly significant increases in duration, occurrence, and coverage, while B showed only a slight prolongation in duration. Conversely, in the diagrammatic axis (DR vs DT), states A and C underwent pronounced reductions, B declined moderately, and D maintained stable duration but decreased in occurrence and coverage.

This study establishes EEG microstates as real-time biomarkers of cognitive overload in software merges, supporting the design of adaptive environments that can adjust abstraction levels or issue high-load alerts. Future work will expand to more realistic merge tasks, include performance measures, integrate multimodal data (e.g., eye-tracking), and refine participant profiling to strengthen validity and clarify whether EEG microstates serve primarily to validate abstraction findings or as a methodological tool in software engineering.

This research is a crucial step toward a more comprehensive plan to enrich the current literature on EEG microstate analysis in software merge tasks.

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