Evaluating Real-Time Adaptive Interfaces through EEG-derived and Self-reported Mental Workload Indicators

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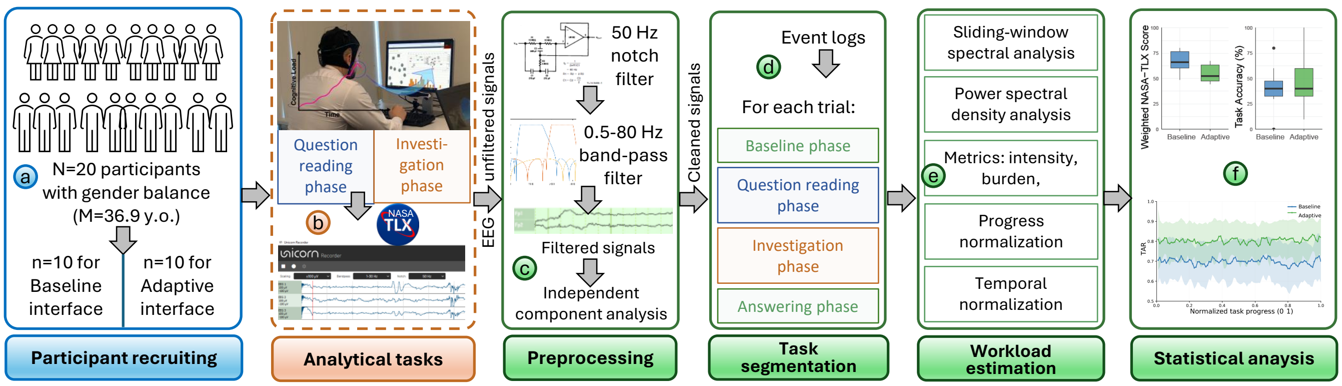

Figure 1: Pipeline of the research methods used in this paper: participant recruiting (a), analytical tasks performed by the participants (b), preprocessing of EEG signals (c) for task segmentation (d), workload estimation (e), and statistical analysis (f).

Abstract

Adaptive information visualization (InfoVis) systems aim to reduce cognitive burden by tailoring the interface to the user's needs. Yet their evaluation typically relies on subjective, post-task measures that lack temporal resolution and may not fully capture nuanced cognitive processes during interaction. We investigate the relationship between subjective workload and electroencephalography (EEG) indicators in the context of real-time adaptive InfoVis dashboards. We conduct a controlled user study ($n = 20$) comparing a baseline (non-adaptive) interface with a real-time adaptive variant, collecting both NASA-TLX ratings and continuous EEG signals. Our results show that adaptivity significantly reduces perceived workload, while EEG measures reveal a consistent tendency toward increased activity in the EEG theta band during task execution. These findings suggest that subjective and physiological measures capture complementary aspects of user cognition, such as perceived effort and sustained attention. We discuss implications for evaluating real-time adaptive InfoVis interfaces and argue for multimodal workload assessment in the engineering of interactive computing systems.

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CCS Concepts

• **Human-centered computing** → **Graphical user interfaces**; **Empirical studies in visualization**; *User centered design*; • **Computer systems organization** → *Real-time systems.*

Keywords

Adaptive interfaces; Adaptivity; Cognitive workload; Electroencephalography; EEG; Information Visualization

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1 Introduction and Background

Information Visualization (InfoVis) dashboards are designed to support analytical reasoning by engaging perceptual mechanisms that make patterns in complex data accessible at a glance [12, 36]. Yet, dashboards can also impose substantial cognitive demands [9, 10] when users must search, compare, and integrate information across multiple coordinated widgets, specially under time pressure [18, 39]. Recent work in user-adaptive InfoVis demonstrates that dashboard effectiveness is shaped not only by design choices but also by the user's cognitive state and individual differences in perceptual and analytical ability [13, 14, 52]. Because static interfaces present the same display to every user regardless of these factors, they risk overloading some users while disempowering others [1]. This problem has motivated a growing interest in adaptive InfoVis systems that modify the interface (either content or presentation, or both) in response to the user's inferred cognitive state [8, 18, 33, 48].

Evaluating whether such adaptations are genuinely helpful requires reliable measurement of the construct they target: *cognitive task workload*. In HCI, the most widely used instrument in user interface (UI) evaluations is the NASA Task Load Index (NASA-TLX) [24, 25], largely because it is quick to administer, straightforward to analyze, and enables comparison with a large body of prior studies [28]. However, the NASA-TLX is a retrospective measure: participants rate their experience only after a task is complete, collapsing any temporal variation in workload into a single aggregate score. It therefore cannot reveal *when* during a task the user was most burdened [46], nor distinguish a brief spike in demand from sustained overload. Furthermore, as a subjective instrument, it is susceptible to individual interpretation biases and expectation effects [6, 29]. Recent reviews have noted both the continued dominance of the NASA-TLX in HCI and the need for complementary measures that offer finer temporal resolution and greater objectivity [6, 28].

Electroencephalography (EEG) is a promising complement because it provides a continuous, objective window into cognitive processing. Well-established neural correlates of task workload include increases in frontal theta power (4–8 Hz) and decreases in parietal alpha power (8–12 Hz) as task demands rise [7, 21, 27]. EEG-based workload indicators have already been used to drive real-time adaptive automation in operationally realistic settings; for example, triggering interface assistance for air traffic controllers when workload exceeded a personalized threshold [5]. Studies combining EEG with subjective measures [20] have shown that the two modalities can provide converging yet non-redundant information about the user's cognitive state [23, 40]. At the same time, there is no agreed-upon method for translating EEG signals into a robust workload estimate: existing approaches range from supervised classifiers trained on labeled calibration data [5], to simple band-power ratios [30], to group-level spectral comparisons across conditions [40]. This lack of standardization makes it difficult to compare or generalize workload estimates across studies, and leaves open the question of which EEG-derived metrics most closely track the workload variations that subjective instruments capture.

In this paper, we examine whether EEG-derived workload metrics (Figure 1) can serve as a useful complement to the NASA-TLX for evaluating real-time adaptive interfaces (Figure 2). We compare two conditions: a baseline (non-adaptive) interface and its adaptive variant that applies visual encodings in real time according to *ergonomic criteria* [11] and *linguistic levels* [37, 47] under five adaptation categories: (1) Color, (2) Size, (3) Proximity, (4) Line thickness, and (5) Shape.

Participants completed five analytical tasks while wearing an EEG headset and reported workload via weighted NASA-TLX after completing each task. To account for individual differences in baseline neural activity, EEG workload is computed relative to a short pre-task fixation period for each user and task; see Section 2.2. We then derive four EEG-based workload indicators and compare their trends against NASA-TLX scores. This design allows us to address three research questions:

- **RQ1:** To what extent do NASA-TLX and EEG-derived workload indicators exhibit convergent trends across interface conditions?
- **RQ2:** Does UI adaptation reduce workload on both subjective and objective metrics?
- **RQ3:** How useful are EEG-derived workload indicators as a complement for evaluating adaptive UIs?

Beyond empirical findings, this work contributes an evaluation perspective for adaptive interfaces by systematically comparing subjective and physiological workload signals across multiple operationalizations. This perspective aligns with engineering needs for multi-metric validation of user behavior, particularly in data-driven and context-aware adaptive interfaces.

2 Research Method

2.1 Participants and Experimental Setup

Twenty participants aged 24–64 years (M = 36.9, SD = 13.13) were recruited through university mailing lists. Self-reported gender was balanced, with 10 participants identifying as male and 10 as female. Participants had a range of professional and academic backgrounds, including secretarial staff (n = 1), administrative staff (n = 2), accountants (n = 2), professors (n = 4), researchers (n = 7), and graduate students (n = 4). All participants reported at least general computer literacy, and two participants had prior experience using InfoVis dashboards in their work (one participated in the Baseline and the other in the Adaptive condition). Participants were randomly assigned to only one experimental condition (between-subjects design): *baseline interface* (n = 10) and *adaptive interface* (n = 10). Each participant completed five tasks, where each corresponded to a question requiring analytical reasoning (see Figure 3 for an example) while interacting with the InfoVis dashboard.

After completing each task, participants reported their perceived workload using the standard NASA-TLX questionnaire. The interface presented multiple coordinated widgets, featuring a timeline, a network graph, and a distribution chart; see Figure 2. These widgets were intended to provide complementary perspectives on the underlying data and support analytical reasoning.

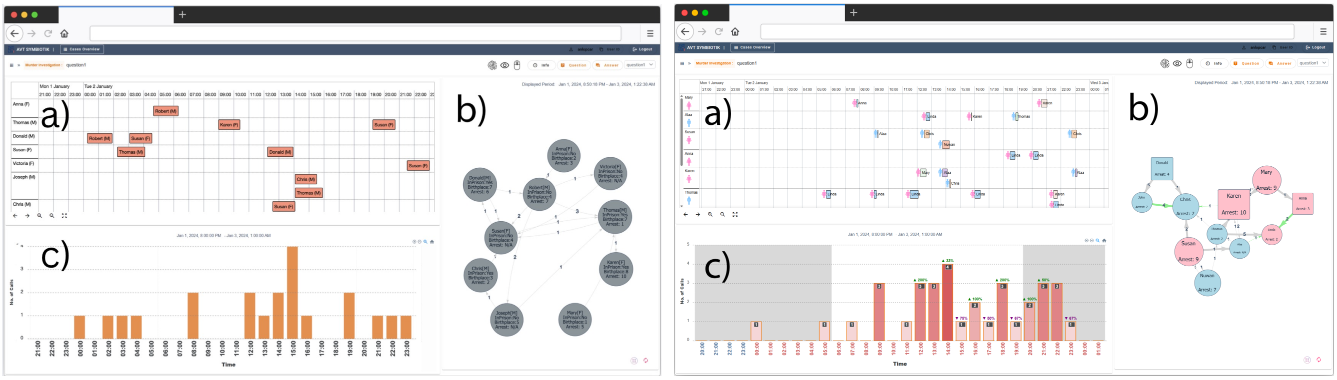

Figure 2: Baseline (left) and adapted (right) dashboards, showing timeline (a), network graph (b), and distribution chart (c).

Each task consisted of two main phases. In the *question reading* phase, participants were presented with the task description (e.g. Figure 3) and were allowed to read and understand it at their own pace. Then they proceeded to the *investigation* phase, during which they explored the InfoVis interface to solve the task.

As hinted before, the adaptive interface applied a set of visual encodings, aimed at reducing visual search and cognitive load, including for example changing background colors to highlight nodes with high connectivity in the network graph, thickening timeline event markers, etc. Each without altering the underlying interface contents.

Given the exploratory nature of this work, the change of visual encodings were performed at random and at different intervals (5, 10, 20, 30, or 60 seconds), without any animated transition to not affect workload [15]. This deliberate design choice allowed us to isolate the presence of adaptation as an independent variable, thus decoupling interface change from any specific triggering logic rather than to evaluate a particular adaptation policy, which could be based e.g. on unsupervised learning [17]. We note that investigating principled, cognitive-state-driven triggering strategies is an explicit direction for future work; see Section 5.

2.2 EEG Preprocessing and Task Segmentation

EEG signals were recorded continuously during the experiment using a Unicorn hybrid black 8-channel headset [41] and processed offline prior to analysis. To suppress power-line interference, a 50 Hz notch filter was applied. The signals were subsequently band-pass filtered between 0.5 Hz and 80 Hz to remove slow drifts and high-frequency noise. Artifact-related activity was further mitigated using independent component analysis (ICA) [51], through which components corresponding to ocular and muscle artifacts were removed. The resulting cleaned signals were analyzed.

Each trial was segmented according to the task event logs. Four phases were identified: (1) a pre-task *baseline phase*, (2) a *question reading phase*, (3) an *investigation phase*, and (4) an *answering phase*. The baseline segment corresponded to the 15 s interval immediately preceding task onset and served as the reference for baseline-relative EEG signal transformations; see Section 2.3. The question reading phase spanned the interval between opening and closing the question prompt. The investigation phase began after the reading phase and ended when answer entry started, excluding both the reading and answering intervals. The answering phase covered the period between answer entry and answer submission.

We observed that the most consistent condition-related neural differences occurred during the *investigation phase*, corresponding to active visual exploration and information search. Consequently, the primary EEG analyses reported in this paper focus on this phase only.

Prompt: A heist occurred between 14:00 and 15:30 in Brussels. The main perpetrator had been arrested twice previously. The police suspected that the perpetrator was instructed over the phone during the heist by someone related to him who was currently in prison. More than four calls were exchanged between them before, during, and after the crime.

Goal: You have to identify the exact time range during which the call between the perpetrator and the imprisoned relative occurred during the heist.

Solution: The call was between 14:15 and 14:45.

Figure 3: Task example. Participants saw only the *Prompt* and *Goal* parts.

2.3 EEG-based Workload Indicators

Temporal variations in neural activity were quantified using a sliding-window spectral analysis. Power spectral density (PSD) was estimated using Welch's method with a 5 s window and a 2.5 s step size. Spectral power was computed in the theta (θ, 4–8 Hz), alpha (α, 8–12 Hz), and beta (β, 13–30 Hz) bands. Following prior literature that links frontal θ increases and posterior α decreases to cognitive effort and sustained attention [16, 31, 43, 44], neural engagement was characterized from the relative contribution of these bands. Theta power was averaged across frontal-central electrodes, whereas alpha power was averaged across posterior electrodes. On the one hand, the bounded *Theta-Alpha Ratio* (TAR) is defined as [44]:

$$\mathrm{TAR} = \frac{\theta}{\theta + \alpha} \tag{1}$$

This formulation constrains the metric to the interval $[0, 1]$, reduces sensitivity to extreme ratio values, and provides an interpretable measure in which larger values indicate stronger relative θ-band dominance and, in the present context, greater task-related neural engagement. Importantly, TAR is interpreted as an index of neural engagement rather than perceived workload [16]. On the other hand, we also compute *Engagement Index* as follows [31, 42, 44]:

$$\text{Engagement} = \frac{\beta}{\theta + \alpha} \quad (2)$$

which is also a popular metric to quantify neural engagement from EEG signals. Previous studies show that it can effectively distinguish between neural states with high accuracy [2, 3, 38], so we report it for the sake of completeness.

To further quantify workload-related indicators from EEG, two complementary formulations were derived from TAR, following the research literature. Let $\text{TaskFeature}_{u,q,t}$ denote the EEG-derived feature for user u, task q, and window t, and let BaselineFeature_u denote the corresponding baseline estimate derived from the pre-task baseline windows. We compute *Log-ratio Mental Work Load* (MWL) [4] and *Burden* [4, 40] as follows:

$$\text{MWL}_{u,q,t} = \log\left(\frac{1 + \text{TaskFeature}_{u,q,t}}{1 + \text{BaselineFeature}_u}\right) \quad (3)$$

where $\mu_{\text{baseline},u}$ and $\sigma_{\text{baseline},u}$ denote the mean and standard deviation of the baseline windows for that trial.

$$\text{Burden}_{u,q} = \sum_{t=1}^{T_{u,q}} z_{u,q,t} \Delta t \quad (4)$$

which captures the cumulative deviation from the baseline state across the task duration, where

$$z_{u,q,t} = \frac{\text{TaskFeature}_{u,q,t} - \mu_{\text{baseline},u}}{\sigma_{\text{baseline},u}} \quad (5)$$

is the per-trial z-score normalization, where $\mu_{\text{baseline},u}$ and $\sigma_{\text{baseline},u}$ denote the mean and standard deviation, respectively, of the baseline windows for that trial.

Taken together, these indicators reinterpret neural engagement dynamics as workload-related indicators, enabling comparison with subjective workload measures such as NASA–TLX.

2.4 Temporal Normalization and Analysis

Because investigation durations varied across trials, direct temporal comparisons between participants are not straightforward. To enable comparable workload trajectories, each trial was normalized to *relative task progress*:

$$\text{Progress} = \frac{t}{T_{u,q}} \quad (6)$$

where t denotes the time of an EEG window and $T_{u,q}$ represents the total duration of the investigation phase for user u on task q. This transformation thus maps each trial to the interval $[0, 1]$.

For analysis and visualization, the normalized progress axis was discretized into equally-spaced bins. User-level workload values were first computed within each bin and then averaged across participants. This procedure avoids bias toward participants with longer exploration durations and yields a duration-invariant representation of workload evolution. All EEG visualizations aggregate results across tasks. Statistical comparisons were conducted using Welch's two-sample t-tests and Hedges' g to report effect sizes.

3 Results

We report results during the investigation tasks. Subjective workload was quantified using the weighted NASA–TLX score post-task, whereas EEG-derived indicators were computed from engagement-related spectral dynamics during the investigation phase and later transformed into the previously mentioned workload-related indicators.

3.1 Subjective Workload

Subjective workload differed significantly between both interface conditions. Participants interacting with the adaptive interface reported lower perceived workload than those using the baseline interface. As shown in Figure 4, the mean weighted NASA–TLX score decreased from $M = 64.56$ ($SD = 8.81$) in the non-adaptive interface to $M = 56.81$ ($SD = 8.09$) in the adaptive interface. This reduction was statistically significant ($t(35.74) = 2.82$, $p = .008$) with a large effect size ($g = 0.90$). The distributional patterns illustrated in the box plots indicate a consistent downward shift of workload ratings across participants, suggesting that the adaptive interface reduced perceived cognitive demand during tasks. Interestingly, users finished tasks faster with the adaptive interface: $M = 4.5$ ($SD = 0.5$) vs. $M = 3.9$ ($SD = 1.1$) minutes in Baseline vs. Adaptive conditions, respectively. The differences were not statistically significant ($t(12.27) = 1.29$, $p = .221$), with a moderate-to-large effect size ($g = 0.58$).

3.2 Neural Engagement Dynamics

Neural engagement, understood as focused and sustained attention during the visual investigation tasks, was primarily examined using the bounded TAR metric. Figure 5 shows the temporal trajectory of this metric across normalized task progress. Across the investigation phase, the adaptive interface exhibited consistently higher TAR values compared with the baseline interface. At the participant level, the overall mean TAR increased from $M = 0.70$ ($SD = 0.17$) in the non-adaptive interface to $M = 0.80$ ($SD = 0.15$) in the adaptive interface. However, the difference was not statistically significant ($t(17.84) = -1.48$, $p = .16$), with a moderate-to-large effect size ($g = 0.63$). A comparable pattern was observed when summarizing the trajectories using the area under the curve, indicating a consistent tendency toward higher θ-dominant neural engagement during investigation in the adaptive interface.

3.3 Complementary Workload Indicators

To evaluate the robustness of the observed engagement patterns, we considered the additional EEG-derived workload indicators introduced in Section 2.3. The results are summarized in Figure 6.

Log-ratio MWL and Burden revealed lower workload-like values under the adaptive interface, whereas Engagement Index indicated elevated values relative to the non-adaptive interface. These differences reflect the distinct properties of the metrics; for example Log-ratio MWL emphasizes relative task-to-baseline change and Burden reflects cumulative workload across the task duration. This analysis confirms that the adaptive interface altered the temporal dynamics of neural engagement during visual investigation rather than producing a uniform shift across all workload metrics.

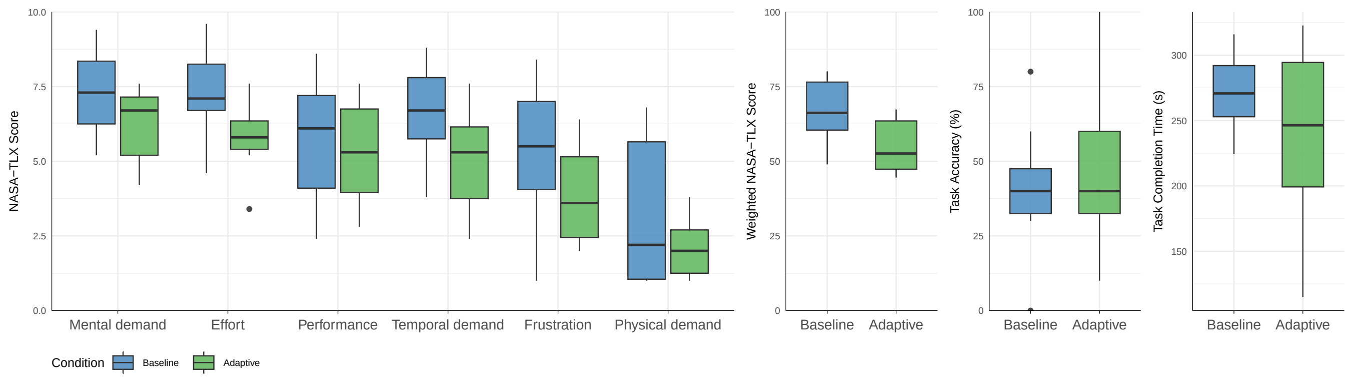

Figure 4: NASA-TLX ratings on each dimension (left) and weighted mental workload (center); lower is better. The rightmost plot shows answer correctness; higher is better.

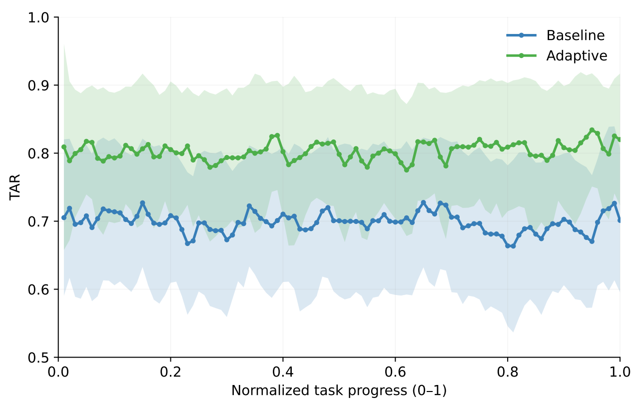

Figure 5: Temporal evolution of EEG cognitive engagement during the investigation phase. Shaded regions represent 95% confidence intervals.

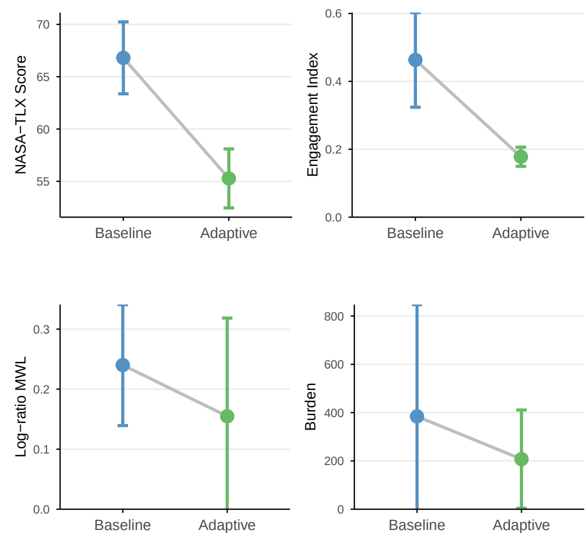

Figure 6: Comparison of subjective workload and EEG-derived workload indicators across baseline (non-adaptive) and adaptive interfaces. Error bars indicate standard error of the mean (SEM). Lower values indicate lower cognitive load.

4 Discussion

We have found convergent trends from subjective (self-reported) and objective (EEG-derived) indicators of mental workload that suggest that interface adaptation reduces cognitive load during investigative tasks. Together, our results indicate that adaptive interfaces can lower perceived cognitive burden while supporting sustained task-related engagement. In the following we answer our research questions.

RQ1: To what extent do NASA-TLX and EEG-derived workload indicators exhibit convergent trends across interface conditions? Our results suggest partial convergence between subjective workload and EEG-derived indicators. Subjective ratings showed a statistically significant reduction in perceived workload under the adaptive interface. A similar trend was observed in EEG-derived workload indicators, particularly the log-ratio MWL, which also indicated lower workload values under the adaptive condition. In contrast, TAR engagement measures did not show a reduction; instead, they exhibited a tendency toward higher θ-dominant activity during visual investigation. This pattern should not be interpreted as contradictory evidence, but rather as reflecting different aspects of cognitive processing. NASA–TLX reflects retrospective perceived effort after task completion, whereas TAR captures ongoing neural engagement during task execution. Increases in TAR are commonly interpreted as indicators of task-related cognitive engagement and attentional control rather than subjective task difficulty [35, 44, 45, 53]. Consequently, the observed pattern suggests that the adaptive interface reduced perceived effort while maintaining or enhancing task-relevant neural engagement.

RQ2: Does UI adaptation reduce workload on both subjective and objective metrics? The subjective workload results provide strong evidence that the adaptive interface reduced perceived cognitive load. Participants reported significantly lower weighted NASA–TLX scores under the adaptive condition, with a large effect size. This indicates that the adaptive interface made the tasks feel less demanding from a user-experience perspective. The EEG results provide a complementary interpretation. Although the temporal TAR differences did not reach statistical significance, the direction of the effect was consistent across comparisons. The observed trend suggests that the adaptive interface supported sustained attentional engagement during information search rather than reducing neural processing. We elaborate more on these findings in Section 4.1.

RQ3: How useful are EEG-derived workload indicators as a complement for evaluating adaptive UIs? Our findings highlight the value of EEG-derived indicators as complementary metrics in adaptive UI evaluation. While NASA–TLX provides a concise post-task assessment of perceived workload, EEG offers a temporally resolved view of cognitive engagement during interaction. The temporal TAR analysis (Section 3.2) revealed how neural engagement evolved throughout the investigation phase and the complementary workload indicators (Section 2.3) demonstrate that different operationalizations of the EEG signal capture distinct aspects of neural activity. These provide multiple perspectives on the underlying cognitive processes during visual exploration.

4.1 Implications of Findings

A critical consideration in interpreting these findings is that EEG frequency bands are not strictly inversely related. Rather, oscillatory activity in the θ, α, and β bands co-varies as a function of task demands, such that ratio-based metrics reflect their relative spectral balance rather than isolated band-specific effects [19, 42]. It is worth remarking that our participants performed time-bounded (5 min) visual information search tasks, characterized by exploratory behavior and moderate cognitive demands, without strong time pressure or stress-inducing constraints. Under such conditions, the research literature [16, 22, 34] associates increases in frontal θ power and decreases in posterior α power with sustained attention and task engagement rather than elevated cognitive load. Accordingly, the increased θ-dominant activity observed in the adaptive interface, as captured by TAR, is interpreted as reflecting enhanced attentional engagement during task execution.

The functional interpretation of EEG spectral components is inherently context-dependent. In more demanding paradigms (e.g., mental arithmetic or complex problem solving), concurrent increases in both θ and β activity have been reported to reflect the joint involvement of working memory, executive control, and active processing [26, 32, 49, 50]. This highlights that band-specific interpretations must be considered in relation to task demands.

Regarding β-based indices, such as Equation 2, our results suggest that the β band contributes minimally to condition-wise differences. Instead, observed variations are primarily driven by the θ (and to a lesser extent α) band, while the β band activity remained relatively stable. This is consistent with the task design, which does not strongly engage processes typically associated with β dynamics, such as motor activity or high-frequency processing. Therefore, although β-based metrics are reported for completeness, their interpretability in this context is limited.

Finally, the bounded TAR formulation (Equation 1) improves interpretability and comparability by constraining it to the $[0, 1]$ range while preserving its role as an index of relative θ dominance, which is the most relevant band to consider in our study. Together, our findings suggest that subjective measures can capture perceived usability improvements, while EEG-derived signals can reveal sustained engagement during interaction. A practical implication is to incorporate both modalities in evaluation pipelines, or to use EEG signals to monitor engagement in real time while validating user experience through post-task measures.

Subjective measures such as NASA-TLX serve as post-task validators, while EEG-derived indicators provide continuous, in-session quantification of focused attention and engagement that can feed into a closed-loop real-time adaptation and monitoring pipeline [33]. Concretely, such a pipeline could operate as follows: EEG workload is estimated per sliding window and compared against a per-user baseline; when the signal crosses a personalized threshold, the system selects and applies an available adaptation from a predefined catalogue. Post-session NASA-TLX scores then validate whether the triggered adaptations translated into perceived workload relief.

5 Limitations and Future Work

Our study involved a relatively small user sample, which partially explains the lack of statistical significance in some cases. For example, the observed effect size in Section 3.2 is consistent with an underpowered comparison rather than a true null effect: a post-hoc sensitivity analysis indicates that approximately 28 participants per condition would be required (80% power at $\alpha = .05$). On the other hand, EEG recordings were obtained using a lightweight 8-channel headset, which may constrain the precision of neural workload estimates. Finally, because of our between-subjects design, individual differences in cognitive strategies and InfoVis expertise may have contributed to variability in both subjective and physiological responses.

Future work should replicate our experiment with more participants, to further validate the relationship between subjective and objective workload measures. Another promising direction for future work is to integrate these measures into a closed-loop adaptive system, where real-time cognitive-state-driven triggering strategies can dynamically guide UI adaptations [33]. Our study provide initial evidence for how EEG signals can complement traditional user evaluation metrics.

Acknowledgments

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References

[1] Silvia Abrahão, Emilio Insfrán, Arthur Sluÿters, and Jean Vanderdonckt. 2021. Model-based intelligent user interface adaptation: challenges and future directions. *Softw. Syst. Model.* 20, 5 (2021). doi:10.1007/S10270-021-00909-7

[2] Yusuf Ahmed, Martin Ferguson-Pell, Kim Adams, and Adriana Ríos Rincón. 2025. EEG-based Engagement Monitoring in Cognitive Games. *Sensors* 25, 7 (2025). doi:10.3390/s25072072

[3] Andrea Apicella, Pasquale Arpaia, Mirco Frosolone, Giovanni Improta, Nicola Moccaldi, and Andrea Pollastro. 2022. EEG-based measurement system for monitoring student engagement in learning 4.0. *Sci. Rep.* 12 (2022). doi:10.1038/s41598-022-09578-y

[4] Pietro Aricò, Gianluca Borghini, Gianluca Di Flumeri, Alfredo Colosimo, Stefano Bonelli, Alessia Golfetti, Simone Pozzi, Jean-Paul Imbert, Géraud Granger, Raïlane Benhacene, and Fabio Babiloni. 2016. Adaptive Automation Triggered by EEG-Based Mental Workload Index: A Passive Brain-Computer Interface Application in Realistic Air Traffic Control Environment. *Front. Hum. Neurosci.* 10 (2016), 539. doi:10.3389/fnhum.2016.00539

[5] Pietro Aricò, Gianluca Borghini, Gianluca Di Flumeri, Nicolina Sciaraffa, Alfredo Colosimo, and Fabio Babiloni. 2017. Passive BCI in Operational Environments: Insights, Recent Advances, and Future Trends. *IEEE Trans. Biomed. Eng.* 64, 7 (2017). doi:10.1109/TBME.2017.2694856

[6] Paul Ayres, Joy Yeonjoo Lee, Fred Paas, and Jeroen J. G. van Merriënboer. 2021. The Validity of Physiological Measures to Identify Differences in Intrinsic Cognitive Load. *Front. Psychol.* 12 (2021). doi:10.3389/fpsyg.2021.702538

[7] Anne-Marie Brouwer, Maarten A Hogervorst, Jan B F van Erp, Tobias Heffelaar, Patrick H Zimmerman, and Robert Oostenveld. 2012. Estimating workload using EEG spectral power and ERPs in the n-back task. *J. Neural Eng.* 9, 4 (jul 2012). doi:10.1088/1741-2560/9/4/045008

[8] Andreas Bulling and Thorsten O. Zander. 2014. Cognition-Aware Computing. *IEEE Pervasive Comput.* 13, 3 (2014). doi:10.1109/MPRV.2014.42

[9] Corentin Burnay, Sarah Bouraga, and Mathieu Lega. 2023. When Dashboard's Content Becomes a Barrier - Exploring the Effects of Cognitive Overloads on BI Adoption. In *Proc. Research Challenges in Information Science (RCIS, Lecture Notes in Business Information Processing)*, Selmin Nurcan, Andreas L. Opdahl, Haralambos Mouratidis, and Aggeliki Tsohou (Eds.). doi:10.1007/978-3-031-33080-3_26

[10] Corentin Burnay, Mathieu Lega, and Sarah Bouraga. 2024. Business intelligence and cognitive loads: Proposition of a dashboard adoption model. *Data Knowl. Eng.* 152 (2024). doi:10.1016/J.DATAK.2024.102310

[11] Gaëlle Calvary, Joëlle Coutaz, David Thevenin, Quentin Limbourg, Laurent Bouillon, and Jean Vanderdonckt. 2003. A Unifying Reference Framework for multi-target user interfaces. *Interact. Comput.* 15, 3 (2003). doi:10.1016/S0953-5438(03)00010-9

[12] Stuart K. Card, Jock D. Mackinlay, and Ben Shneiderman. 1999. *Information visualization.* Morgan Kaufmann Publishers Inc. doi:10.1201/b11963

[13] Francesco Chiossi, Johannes Zagermann, Jakob Karolus, Nils Rodrigues, Priscilla Balestrucci, Daniel Weiskopf, Benedikt Ehinger, Tiare Feuchtner, Harald Reiterer, Lewis L. Chuang, Marc Ernst, Andreas Bulling, Sven Mayer, and Albrecht Schmidt. 2022. Adapting visualizations and interfaces to the user. *Inf. Technol.* 64, 4–5 (2022). doi:10.1515/itit-2022-0035

[14] Cristina Conati, Giuseppe Carenini, Dereck Toker, and Sébastien Lallé. 2015. Towards User-Adaptive Information Visualization. In *Proc. AAAI Conf. on Artificial Intelligence*, Vol. 29. doi:10.1609/aaai.v29i1.9775

[15] Charles-Eric Dessart, Vivian Genaro Motti, and Jean Vanderdonckt. 2011. Showing user interface adaptivity by animated transitions. In *Proc. SIGCHI Symposium on Engineering Interactive Computing Systems (EICS '11)*. doi:10.1145/1996461.1996501

[16] Saravanakumar Duraisamy, Nick Roeser, Mateusz Dubiel, and Luis A. Leiva. 2025. An Adaptive Brain-Computer Interface Game with Blink Controls and Cognitive State Monitoring. In *Companion Proc. Intl. Conf. on Intelligent User Interfaces (IUI '25 Companion)*. doi:10.1145/3708557.3716365

[17] Diego Eloi, Alaa Sahraoui, Jean Vanderdonckt, and Luis A. Leiva. 2024. User-controlled Form Adaptation by Unsupervised Learning. In *Adjunct Proc. Nordic Conf. on Human-Computer Interaction (NordiCHI '24 Adjunct)*. doi:10.1145/3677045.3685431

[18] Stephen H. Fairclough. 2009. Fundamentals of physiological computing. *Interact. Comput.* 21, 1–2 (2009). doi:10.1016/j.intcom.2008.10.011

[19] F Garro, E Fenoglio, M Laffranchi, N Garcia-Hernandez, and M Semprini. 2025. Neurophysiological correlates of user engagement in mixed reality exergames. *J. Neural Eng.* 22, 3 (2025). doi:10.1088/1741-2552/addae7

[20] Daniel Gaspar-Figueiredo, Jean Vanderdonckt, Silvia Abrahão, and Emilio Insfrán. 2026. User experience with adaptive user interfaces: Comparing performance and preferences. *J. Syst. Softw.* 231 (2026). doi:10.1016/J.JSS.2025.112598

[21] A Gevins, M E Smith, L McEvoy, and D Yu. 1997. High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. *Cereb. Cortex* 7, 4 (06 1997). doi:10.1093/cercor/7.4.374

[22] Alan Gevins, Michael E Smith, Linda McEvoy, and Daphne Yu. 1997. High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. *Cereb. Cortex* 7, 4 (1997). doi:10.1093/cercor/7.4.374

[23] Thomas C. Hankins and Glenn F. Wilson. 1998. A comparison of heart rate, eye activity, EEG, and subjective measures of pilot mental workload. *Aviat. Space Environ. Med.* 69, 4 (1998).

[24] Sandra G. Hart. 2006. Nasa-Task Load Index (NASA-TLX); 20 Years Later. *Proc. Hum. Factors Ergon. Soc. Annu. Meet.* 50, 9 (2006). doi:10.1177/154193120605000909

[25] Sandra G. Hart and Lowell E. Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In *Human Mental Workload.* Advances in Psychology, Vol. 52. North-Holland. doi:10.1016/S0166-4115(08)62386-9

[26] Kenji Katahira, Yoichi Yamazaki, Chiaki Yamaoka, Hiroaki Ozaki, Sayaka Nakagawa, and Noriko Nagata. 2018. EEG correlates of the flow state: A combination of increased frontal theta and moderate frontocentral alpha rhythm in the mental arithmetic task. *Front. Psychol.* 9 (2018). doi:10.3389/fpsyg.2018.00300

[27] Wolfgang Klimesch. 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res. Rev.* 29, 2 (1999). doi:10.1016/S0165-0173(98)00056-3

[28] Thomas Kosch, Jakob Karolus, Johannes Zagermann, Harald Reiterer, Albrecht Schmidt, and Paweł W. Woźniak. 2023. A Survey on Measuring Cognitive Workload in Human-Computer Interaction. *ACM Comput. Surv.* 55, 13s (2023). doi:10.1145/3582272

[29] Thomas Kosch, Robin Welsch, Lewis Chuang, and Albrecht Schmidt. 2023. The Placebo Effect of Artificial Intelligence in Human–Computer Interaction. *ACM Trans. Comput. Hum. Interact.* 29, 6 (2023). doi:10.1145/3529225

[30] Naveen Kumar and Jyoti Kumar. 2016. Measurement of Cognitive Load in HCI Systems Using EEG Power Spectrum: An Experimental Study. In *Proc. Intl. Conf. Intelligent Human Computer Interaction (IHCI '16, Vol. 84)*. doi:10.1016/j.procs.2016.04.068 Procedia Computer Science.

[31] Ivo Käthner, Selina C. Wriessnegger, Gernot R. Müller-Putz, Andrea Kübler, and Sebastian Halder. 2014. Effects of mental workload and fatigue on the P300, alpha and theta band power during operation of an ERP (P300) brain–computer interface. *Biol. Psychol.* 102 (2014). doi:10.1016/j.biopsycho.2014.07.014

[32] Chun-Ling Lin, Melody Jung, Ying Choon Wu, Chin-Teng Lin, and Hsiao-Ching She. 2012. Brain dynamics of mathematical problem solving. In *Proc. IEEE Annual Intl. Conf. Engineering in Medicine and Biology Society (EMBC '12)*. doi:10.1109/EMBC.2012.6347033

[33] Angela Lopez-Cardona, Mireia Masias Bruns, Nuwan T. Attygalle, Sebastian Idesis, Matteo Salvatori, Konstantinos Raftopoulos, Konstantinos Oikonomou, Saravanakumar Duraisamy, Parvin Emami, Nacera Latreche, Alaa Eddine Anis Sahraoui, Michalis Vakalellis, Jean Vanderdonckt, Ioannis Arapakis, and Luis A. Leiva. 2025. Context-Aware Adaptive Visualizations for Critical Decision Making. In *Proc. ECAI*. doi:10.3233/faia251433

[34] Timothy McMahan, Ian Parberry, and Thomas D Parsons. 2015. Evaluating Electroencephalography Engagement Indices During Video Game Play. In *Proc. Foundations of Digital Games Conference (FDG '15)*.

[35] Davide V Moretti. 2015. Theta and alpha EEG frequency interplay in subjects with mild cognitive impairment: evidence from EEG, MRI, and SPECT brain modifications. *Front. Aging Neurosci.* 7 (2015). doi:10.3389/fnagi.2015.00031

[36] Tamara Munzner. 2014. *Visualization Analysis and Design.* A K Peters/CRC Press, Boca Raton, FL. doi:10.1201/b17511

[37] Jakob Nielsen. 1986. A virtual protocol model for computer-human interaction. *Int. J. Man-Mach. Stud.* 24, 3 (1986). doi:10.1016/S0020-7373(86)80028-1

[38] Joseph K. Nuamah, Younho Seong, and Sun Yi. 2017. Electroencephalography (EEG) classification of cognitive tasks based on task engagement index. In *Proc. Cognitive and Computational Aspects of Situation Management (CogSIMA '17)*. doi:10.1109/COGSIMA.2017.7929581

[39] Robert E. Patterson, Leslie M. Blaha, Georges G. Grinstein, Kristen K. Liggett, David E. Kaveney, Kathleen C. Sheldon, Paul R. Havig, and Jason A. Moore. 2014. A human cognition framework for information visualization. *Comput. Graph.* 42 (2014). doi:10.1016/j.cag.2014.03.002

[40] Kerstin Pieper, Robert P. Spang, Pablo Prietz, Sebastian Möller, Erkki Paajanen, Markus Vaalgamaa, and Jan-Niklas Voigt-Antons. 2021. Working With Environmental Noise and Noise-Cancelation: A Workload Assessment With EEG and Subjective Measures. *Front. Neurosci.* 15 (2021). doi:10.3389/fnins.2021.771533

[41] Matthew B. Pontifex and Colt A. Coffman. 2023. Validation of the g.tec Unicorn Hybrid Black wireless EEG system. *Psychophysiology* 60, 9 (2023). doi:10.1111/psyp.14320

[42] Alan T Pope, Edward H Bogart, and Debbie S Bartolome. 1995. Biocybernetic system evaluates indices of operator engagement in automated task. *Biol. Psychol.* 40, 1-2 (1995). doi:10.1016/0301-0511(95)05116-3

[43] Sébastien Puma, Nadine Matton, Pierre-V. Paubel, Éric Raufaste, and Radouane El-Yagoubi. 2018. Using theta and alpha band power to assess cognitive workload in multitasking environments. *Int. J. Psychophysiol.* 123 (2018). doi:10.1016/j.ijpsycho.2017.10.004

[44] Bujar Raufi and Luca Longo. 2022. An evaluation of the EEG alpha-to-theta and theta-to-alpha band ratios as indexes of mental workload. *Front. Neuroinform.* 16 (2022). doi:10.3389/fninf.2022.861967

[45] Revati Shriram, Mahalingam Sundhararajan, and Nivedita Daimiwal. 2013. EEG based cognitive workload assessment for maximum efficiency. *Int. Organ. Sci. Res.* 7 (2013).

[46] Kashyap Todi, Gilles Bailly, Luis A. Leiva, and Antti Oulasvirta. 2021. Adapting User Interfaces with Model-based Reinforcement Learning. In *Proc. SIGCHI Conf. on Human Factors in Computing Systems (CHI)*. doi:10.1145/3411764.3445497

[47] Jean Vanderdonckt. 1995. Accessing Guidelines Information with Sierra. In *Proc. IFIP TC13 Int. Conf. on Human-Computer Interaction (Interact '95)*, Knut Nordby, Per Helmersen, David J. Gilmore, and Svein A. Arnesen (Eds.). doi:10.1007/978-1-5041-2896-4_52

[48] Jean Vanderdonckt, Sara Bouzit, Gaëlle Calvary, and Denis Chêne. 2019. Exploring a Design Space of Graphical Adaptive Menus: Normal vs. Small Screens. *ACM Trans. Interact. Intell. Syst.* 10, 1 (2019). doi:10.1145/3237190

[49] S Vieira, JS Gero, V Gattol, J Delmoral, S Li, G Cascini, and A Fernandes. 2022. Designing-related neural processes: Higher alpha, theta and beta bands' key roles in distinguishing designing from problem-solving. In *Design computing and cognition*. Springer. doi:10.1007/978-3-030-90625-2_32

[50] Qiang Wang and Olga Sourina. 2013. Real-time mental arithmetic task recognition from EEG signals. *IEEE Trans. Neural Syst. Rehab. Eng.* 21, 2 (2013). doi:10.1109/TNSRE.2012.2236576

[51] Irene Winkler, Stefan Haufe, and Michael Tangermann. 2011. Automatic classification of artifactual ICA-components for artifact removal in EEG signals. *Behav. Brain Funct.* 7, 1 (2011). doi:10.1186/1744-9081-7-30

[52] Fernando Yanez, Cristina Conati, Alvitta Ottley, and Carolina Nobre. 2025. The State of the Art in User-Adaptive Visualizations. *Comput. Graph. Forum* 44, 1 (2025). doi:10.1111/cgf.15271

[53] Katarzyna Zawiślak-Fornagiel, Daniel Ledwoń, Monika Bugdol, Patrycja Romaniszyn-Kania, Andrzej Małecki, Agnieszka Gorzkowska, and Andrzej W Mitas. 2023. The increase of theta power and decrease of alpha/theta ratio as a manifestation of cognitive impairment in Parkinson's disease. *J. Clin. Med.* 12, 4 (2023). doi:10.3390/jcm12041569