Reducing Cognitive Overload in Software Engineers: A Design Science Approach

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Abstract

Software engineers often face Mental Workload (MWL) challenges, such as burnout and reduced performance, due to the demanding nature of their work. Employers can address these issues by using emerging technology-driven solutions with data-driven dashboards to monitor cognitive load, identify stress points, and prevent burnout. This paper introduces MentalEEG, a web-based MWL monitoring system developed through an iterative Design Science Research methodology to enhance employee well-being in high-demand cognitive environments. MentalEEG integrates subjective self-assessments and EEG data to provide personalized real-time insights for managing MWL. Using large language models (LLMs), its user-centric dashboard offers real-time analytics and recommendations aligned with organizational health guidelines, enabling proactive interventions to prevent burnout and cognitive overload. The study contributes by sharing key lessons learned from the development of MentalEEG, presenting a context framework for organizational-wide mental health insights, and demonstrating the value of integrating LLMs to improve workload monitoring and the well-being of software professionals.

Keywords

Medical Software Evaluation, Software Development, Real-Time Analytics Dashboard, MWL Prevention

1. Introduction

Mental workload(MWL) refers to the cognitive effort required to perform tasks. High mental workload can lead to stress or errors, while too little can indicate under utilization. Mental well-being is essential for software engineers, who frequently experience burnout, reduced performance, and adverse health effects due to the cognitive demands of problem solving, creativity, and individual factors such as age, personality, and expertise [1, 2]. The shift to remote work has further intensified cognitive strain and social isolation, necessitating proactive workload management strategies [3, 4].

Employers can mitigate these challenges by adopting technology-driven solutions like mobile health (mHealth) applications and data-driven dashboards, which have been effective in healthcare for improving patient outcomes [5, 4, 6]. Similarly, real-time analytics dashboards can enable self-monitoring and tracking of cognitive load, offering valuable information on the distribution of workload, stress points, and mental health indicators [7]. These tools empower organizations to prevent burnout, redistribute tasks efficiently, and enhance overall employee well-being.

1.1. Research problem

Current mHealth systems and data visualization tools do not address long-term trends in MWL, especially in cognitively demanding professions [8]. Traditional methods like NASA Task Load Index (NASA-TLX) and Subjective Workload Assessment Technique (SWAT) provide only subjective, individual-level insights with limited real-time applicability [9]. Although wearable technologies enable continuous monitoring, they lack integration for organizational interventions, and the absence of real-time analytics that translate workload data into actionable strategies leaves organizations unable to effectively support employee well-being [10]. Emerging technologies such as Large Language Models (LLM) offer potential

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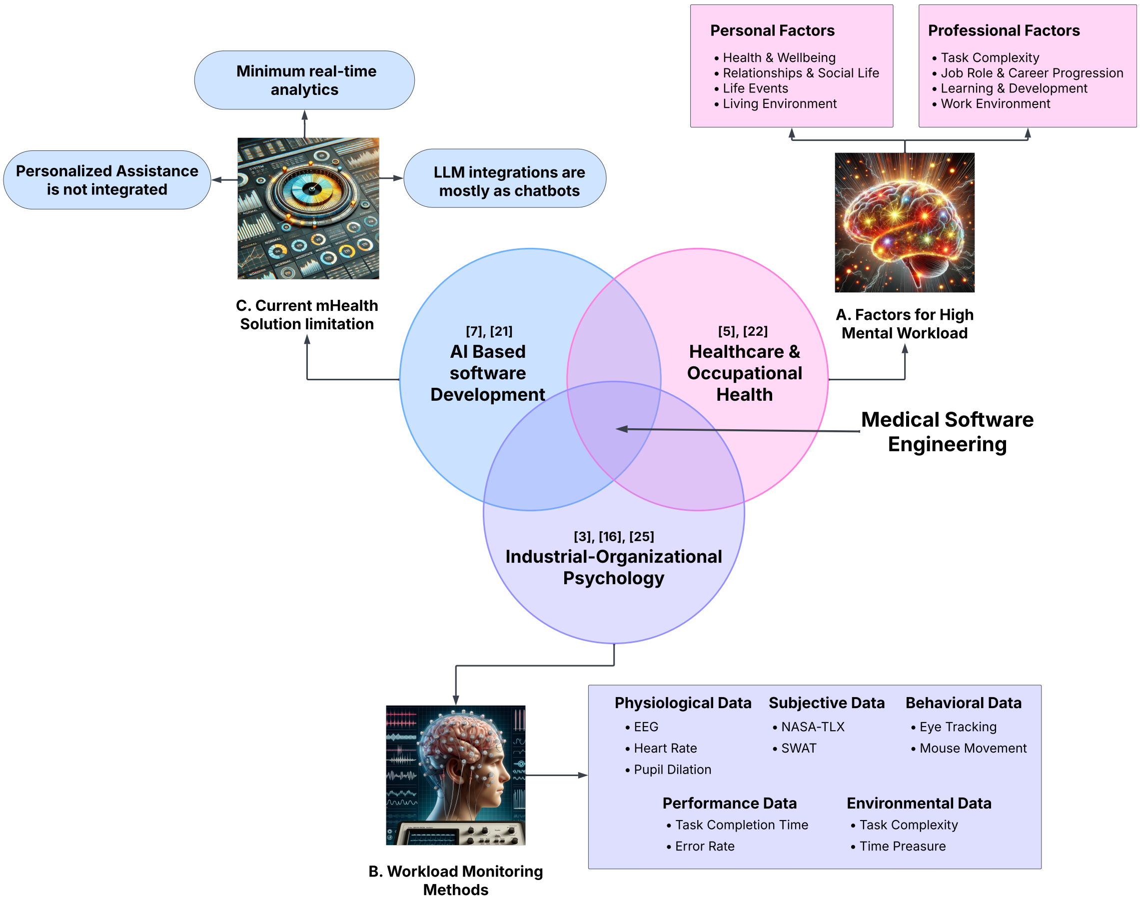

Figure 1: An Interdisciplinary Framework for MWL Monitoring.

by processing biometric and subjective data for personalized, real-time interventions [11]. Yet, there is little research on analytical dashboards that integrate MWL monitoring with LLM-driven organizational insights [1, 2, 3, 4, 5].

Figure 1 illustrates key interdisciplinary dimensions influencing MWL monitoring, including industrial-organizational psychology, AI-driven software development, healthcare, and occupational health. By integrating physiological, subjective, and behavioral data sources, it highlights the limitations of current mHealth solutions and the need for AI-enhanced real-time monitoring systems like MentalEEG to bridge these gaps.

1.2. Research objective and method

The primary objective of this study is to design and develop MentalEEG, a system for real-time monitoring and visualization of employee MWL. Conducted as a university-led initiative, this research aims to support HR departments in managing cognitive workload using data-driven insights. The MentalEEG system focuses on developing a real-time analytics dashboard that stores, analyzes, and visualizes MWL data, providing instant insights based on subjective and biometric data for professionals in cognitively demanding fields like software engineering. It also integrates LLMs to enhance its capabilities in processing and interpreting workload data, offering personalized real-time feedback based on organizational health guidelines to improve employee well-being and productivity [12].

The development follows an initial study framework (see Figure 2 and Section 3), integrating subjective self-reports and objective biometric data (e.g., EEG readings) into a central dashboard. The study adopts the Design Science Research (DSR) methodology [13] to ensure scientific validity and practical applicability, with an iterative approach (see Figure 3) facilitating the integration of advanced technologies like LLMs and real-time workload analytics.

1.3. Research contribution

This study advances the development of medical health software for employee well-being in the high-tech industry by introducing a real-time MWL monitoring approach to mitigate cognitive overload. It offers contributions through lessons learned from MentalEEG's development (see Section 6.1), providing insights into technology selection and balancing system complexity with usability, a refined framework (Figure 5) applicable across industries for effective MWL management, and a demonstration of LLM integration (Figure 6) within the DSR approach, showcasing its potential for real-time MWL monitoring.

2. Background Literature

2.1. Mental workload monitoring in software engineering

MWL is a critical factor in software engineering, where developers perform cognitively demanding tasks like coding, debugging, and problem-solving [1, 2]. Workload is shaped by personal factors (e.g., health, relationships) and professional factors (e.g., task complexity, job roles) [14], making its management vital for productivity and well-being. Traditional tools such as NASA-TLX evaluate MWL across six dimensions but fail to capture real-time cognitive fluctuations [15]. Advances in electroencephalography (EEG) enable dynamic monitoring by detecting theta wave increases (cognitive effort) and alpha wave decreases (relaxation) [16]. However, EEG systems face challenges like low spatial resolution and data interference, necessitating advanced signal processing [17]. Integrating EEG with wearable biosensors offers a promising solution for real-time MWL monitoring in high-demand settings [18].

2.2. Workload monitoring solutions and their limitations

Current mHealth solutions prioritize individual well-being but lack real-time tracking and organizational-level MWL monitoring [8]. They often fail to integrate diverse data sources critical for understanding employee workload [11] or dynamically address fluctuations in high-stress environments. The absence of AI-driven interventions limits their effectiveness [19]. Analytic dashboards, common in medical contexts, simplify complex health data and could be adapted for workforce management, offering real-time insights into mental health and workload trends [6, 7].

2.3. Large language models and mental workload monitoring

Integrating LLMs, such as the OpenAI API, into MWL monitoring systems enhances personalized interventions. Multi-modal LLMs process diverse inputs—text, images, audio, and biometric signals (e.g., EEG, heart rate variability)—to provide a comprehensive view of mental state [20]. This enables accurate real-time workload tracking and tailored recommendations, improving intervention precision and relevance.

3. Study Framework

To achieve the research objectives (Section 1.2), we designed a framework for the MentalEEG system (Figure 2) that defines the interactions between system components and users. The MentalEEG dashboard, the primary interface, processes MWL data from subjective self-assessments and objective biometric sources. A central database stores this data alongside company-specific health guidelines, ensuring recommendations align with organizational well-being policies.

A key feature is the integration of LLMs, which analyze workload data and retrieve guidelines to generate real-time, personalized recommendations tailored to individual and organizational health strategies [21]. The Analytical Views and Data Visualization module presents insights through charts and graphs, facilitating data-driven decision-making.

This framework supports the development of MentalEEG using the Design Science Research (DSR) methodology, detailed in the next section.

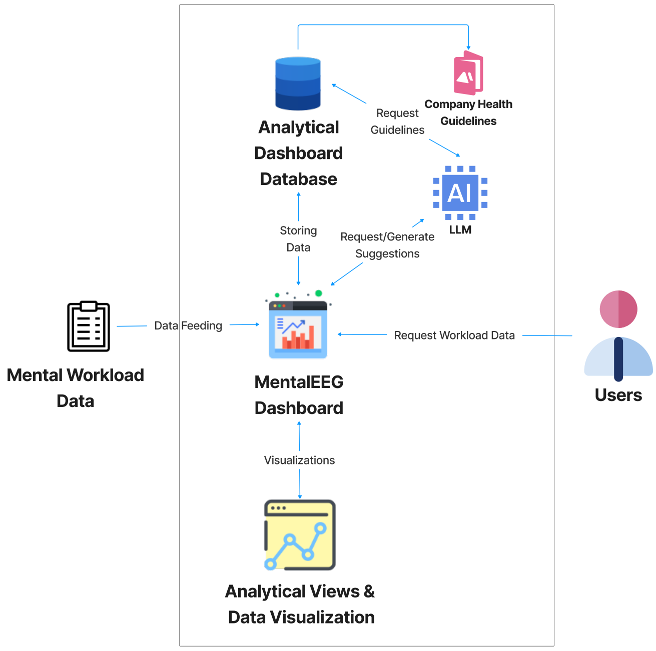

Figure 2: A framework for developing a MWL monitoring system.

4. MentalEEG Artifact Development

To develop the MentalEEG system, we employed the Design Science Research (DSR) methodology outlined by [13], valued for its structured approach to artifact creation and evaluation. This methodology guided three iterative cycles (Section 4.4), facilitating continuous refinement based on stakeholder feedback, as depicted in Figure 3. This process ensured alignment with user needs and enhanced system functionality across iterations.

4.1. Ethics Statement

Participants received study details two weeks prior and provided written consent. Data was anonymized, and participants could withdraw anytime without consequences. The study followed the ethical guideline of the Ethics Committee of Human Sciences of University of Oulu

4.2. Participant Recruitment, Data Collection & Preprocessing

Twelve participants with at least two years of software engineering or IT management experience were recruited from local software companies and a university alumni network (Table 2). EEG data were collected using the EPOC X - 14 Channel Wireless EEG Headset (10-20 system, 256 Hz sampling), synchronized with task performance metrics. Preprocessing, per [22], involved bandpass filtering (1-40 Hz), re-referencing, and channel standardization to optimize signal quality and classification accuracy.

4.3. Likert-Scale EEG Classification Framework

Adapting the Task Load classification from [22], we mapped EEG-derived workload levels to a 1–4 Likert scale aligned with MATB-II task load levels (Table 1). Passive Watching (PW) – Minimal mental workload, Low Load (LL) – A light workload, Medium Load (ML) – A moderate workload, High Load (HL) – A high (or “Hard”) workload level. These four levels reflect increasing cognitive difficulty and demand. The EEG-based classifier was trained on these conditions, so it learns to recognize patterns of brain activity associated with each level of workload. Importantly, these objective categories have been validated against NASA-TLX subjective ratings. In other words, when someone is in a High Load condition per EEG, they also report high workload on NASA-TLX; when they are in Low Load or Passive conditions, they report low NASA-TLX scores.

This post-task NASA-TLX self-reports, validated the EEG-derived Likert scale, showing strong correlation with EEG estimates. This dual validation supports real-time monitoring and proactive interventions.

Table 1
Likert Scale Mapping to MATB-II Task Load Levels

Likert Scale	Task Load Level	NASA-TLX Mean (SD)	EEG Features
1	Passive Watching (PW)	N/A	Low theta/alpha power
2	Low Load (LL)	32.1 (5.2)	Moderate frontal θ increase
3	Medium Load (ML)	43.7 (6.8)	High θ/α ratio
4	Hard Load (HL)	49.8 (7.1)	Peak θ power

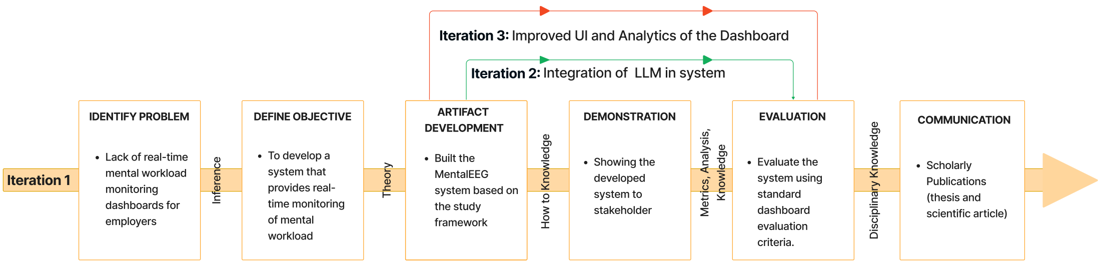

Figure 3: Design science research process of developing the MentalEEG system based on guidelines of Peffers et al. [13]

4.4. Iterations of MentalEEG Artifact (V1,V2,V3)

The first iteration (V1) established core functionalities using Next.js, Django, and Firebase, including employee profile management, workload tracking (1–4 Likert scale), and a dashboard for trend visualization (Figure 4). Stakeholder feedback from a demonstration validated the structure but emphasized needs for advanced analytics and real-time monitoring.

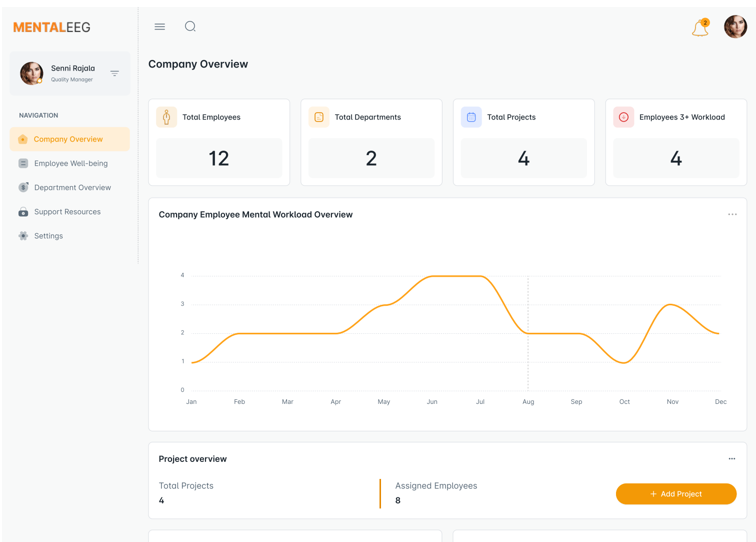

Figure 4: Screenshot of initial MentalEEG system (Iteration 1).

The second iteration (V2) integrated an AI-powered recommendation system using LangChain and OpenAI API with Retrieval Augmented Generation (RAG) [21]. This enabled personalized support actions based on workload history and company guidelines. Stakeholders appreciated the contextual recommendations but requested enhanced data visualization, shaping the next phase.

The third iteration (V3) enhanced analytics with department-level insights, team workload balancing, and customizable guidelines, supported by Chart.js visualizations. System optimizations included caching, real-time updates, and security enhancements. Usability testing with 12 participants (Table 2) assessed workflow, engagement, and utility [23], ensuring workplace applicability while balancing complexity and usability.

5. Evaluation of MentalEEG Artifact

Table 2
Participant Demographics and Study Involvement

ID	Role	Experience	Org Type	Iterations	Workload Level
U1	Full-Stack Developer	5 yrs	Fintech	I1, I3	3 (Moderate)
U2	HR Business Partner	8 yrs	Enterprise	I1, I3	4 (High)
U3	DevOps Lead	4 yrs	Cloud	I1, I3	2 (Low)
U4	UX Engineer	3 yrs	HealthTech	I1, I3	4 (High)
U5	Engineering Manager	10 yrs	E-commerce	I1, I3	3 (Moderate)
U6	Backend Architect	7 yrs	AI Startup	I1, I3	1 (Very Low)
U7	ML Ops Engineer	6 yrs	HealthTech	I1, I3	4 (High)
U8	Frontend Tech Lead	4 yrs	EdTech	I1, I3	2 (Low)
U9	Junior Developer	1 yr	Academic	I1, I3	4 (High)
U10	QA Automation Lead	5 yrs	Fintech	I1, I3	3 (Moderate)
U11	Data Engineering Lead	9 yrs	Analytics	I1, I3	1 (Very Low)
U12	Director of Engineering	12 yrs	Enterprise	I1, I2, I3	4 (High)

The MentalEEG system was evaluated over three iterations using the dashboard evaluation framework by [23]. Twelve participants from diverse software-related roles (Table 2) interacted with the system for 20 minutes per iteration, followed by an interview and a structured questionnaire (Table 3) assessing usability and functionality across interaction workflow (IW), perceived engagement (PE), and potential utility (PU) [23].

The interaction workflow evaluation, focusing on navigation ease and efficiency [23], showed that 83% of participants (10 of 12) found the dashboard intuitive, with U2, U3, U4, and U5 particularly praising the accessibility of features like the company-wide workload overview. However, U7 struggled with settings access during real-time operations, and U9 found section transitions confusing, highlighting areas for refinement.

Perceived engagement, assessing visual appeal and data interaction [23], indicated that 92% of participants (11 of 12) appreciated the interface's clean layout and clear charts, as noted by U2, U4, and U5. U7, however, criticized unclear color choices. For overall experience (Q3), 42% rated it "Good", while 25% (U9, U11, U3) were neutral, suggesting enhancements in navigation and functionality.

Potential utility, evaluating decision-making relevance [23], was endorsed by 83% of participants (10 of 12), who valued real-time insights, as highlighted by U1, U2, and U5. U3 and U7 expressed doubts about its applicability across roles, and while 42% found it intuitive, 17% (U3, U7) struggled with its focus and features.

Table 3
Questionnaire for Dashboard Evaluation [23]

Questions	Response Type	Criteria
Q1: Do you find the MentalEEG dashboard layout easy to navigate for your specific needs?	Yes/No/Maybe	IW
Q2: Do you find the MentalEEG interface visually appealing?	Yes/No/Maybe	PE
Q3: How would you describe your overall user experience with using the dashboard?	1–5 Likert	PE
Q4: Do you think the MentalEEG dashboard could be useful for decision-making in a professional setting?	Yes/No/Maybe	PU
Q5: Please rate your overall impression of the MentalEEG Analytical Dashboard.	1–5 Likert	PU

Table 4
Evaluation Summary for MentalEEG System

Criteria	Findings	Improvements
Interaction Workflow	• 83% found navigation easy • U7: Settings access issues • U9: Confusing transitions	• Dedicated settings panel added • Simplified section transitions
Perceived Engagement	• 92% found interface appealing • U7: Color contrast issues • 25% neutral on navigation	• Enhanced color contrast • Dark mode implemented • Layout hierarchy optimized
Potential Utility	• 83% reported decision-making is valuable • U3/U7: Context-awareness concerns	• Role-specific recommendations • AI explanation module added

6. Results and Lessons Learned

6.1. Lessons Learned from Iterations

The development of the MentalEEG system followed an iterative, feedback-driven approach under the Design Science Research (DSR) methodology, with each iteration introducing new functionalities and refinements to address technical and usability challenges. Below are the key lessons learned from each phase.

The first iteration established core functionalities for real-time workload monitoring, adopting Next.js over Flutter for its scalability and React ecosystem integration. Data collection from 12 participants using a 14-channel EEG headset and NASA-TLX faced challenges with signal consistency and scheduling, resolved through testing and flexible timing. Stakeholders feedback validated the dashboard's usability but emphasized the need for AI-driven features, shaping subsequent iterations.

The second iteration introduced an AI-powered recommendation system using LangChain and the OpenAI API with Retrieval Augmented Generation (RAG) [21]. Fine-tuning the LLM ensured accurate guideline interpretation, delivering context-sensitive recommendations. Stakeholders valued the quick responses but requested enhanced visualization, guiding the focus of the next phase toward analytics and UI improvements.

The third iteration enhanced the dashboard with department-level analytics and team workload balancing, visualized using Chart.js. Performance was optimized through caching and API rate limiting, while usability testing with 12 participants confirmed workplace relevance. Stakeholders praised the analytics but suggested further scalability and responsiveness enhancements, highlighting the balance between AI complexity and usability. The iterative process evolved MentalEEG into a scalable tool for employee well-being, emphasizing stakeholder input and intuitive design.

6.2. Refined Framework for Developing a Mental Workload Monitoring System

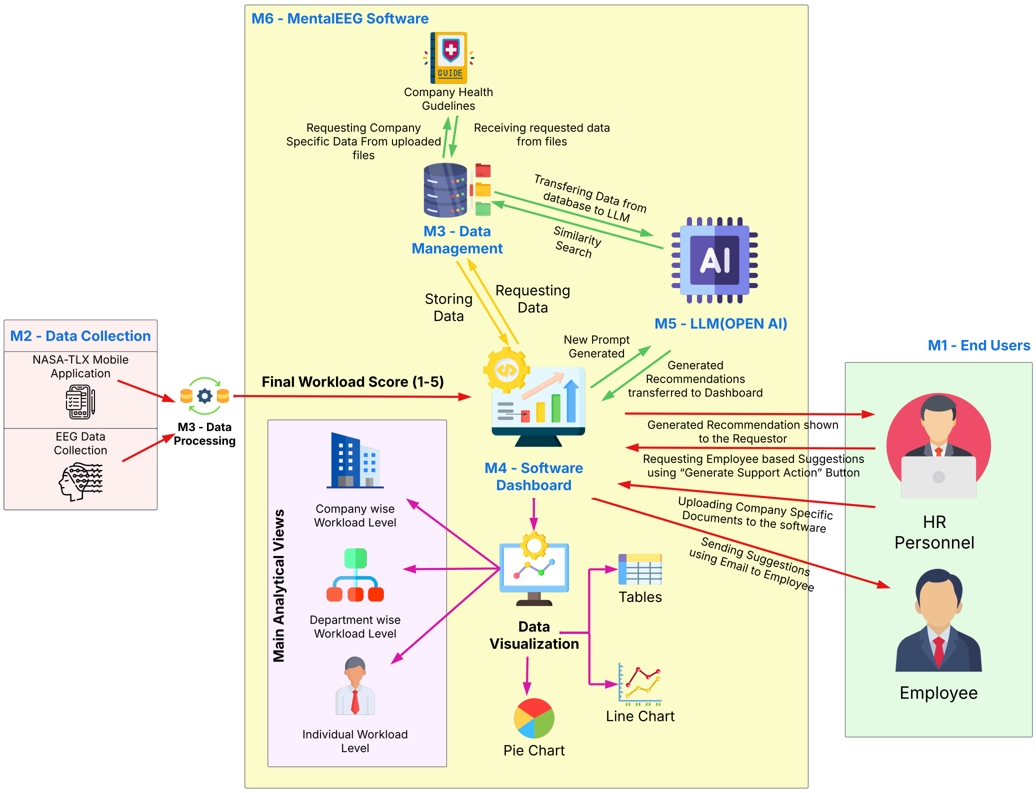

Figure 5: Refined framework with its modules for developing a MWL monitoring system.

The refined framework (Figure 5), evolved from Section 2.2, integrates advanced analytics and AI-driven insights to overcome limitations in MWL monitoring. Primary users [M1]—HR professionals and line managers monitor trends, while employees benefit indirectly from actionable insights. Data collection [M2] combines subjective NASA-TLX and objective EEG sources, offering flexibility for varied organizational capabilities. An ETL pipeline [M3] processes data into a real-time database, enabling accurate decision-making. The display system [M4] visualizes trends with descriptive analytics (e.g., bar and line graphs), with potential for future predictive models. Large Language Models [M5] drive real-time, policy-aligned recommendations through RAG, and the MentalEEG software [M6] provides an interactive interface for managing well-being and productivity.

7. Discussion

Discussion section assesses how MentalEEG fulfills its research objectives by delivering real-time, actionable insights through integrated subjective and objective data, enhanced by OpenAI API for personalized interventions. It examines practical implications for organizational well-being and productivity, discusses study limitations, and suggests future research directions.

7.1. Addressing the Research Objectives

7.1.1. Real-Time Analytical Dashboard

MentalEEG meets the first research objective (Section 1.2) by integrating EEG data with self-assessments to provide context-sensitive, real-time interventions. This approach bridges gaps in existing tools [18, 1], offering a scalable, data-driven system tailored for high-stress sectors like software engineering.

7.1.2. LLM Integration into Dashboard

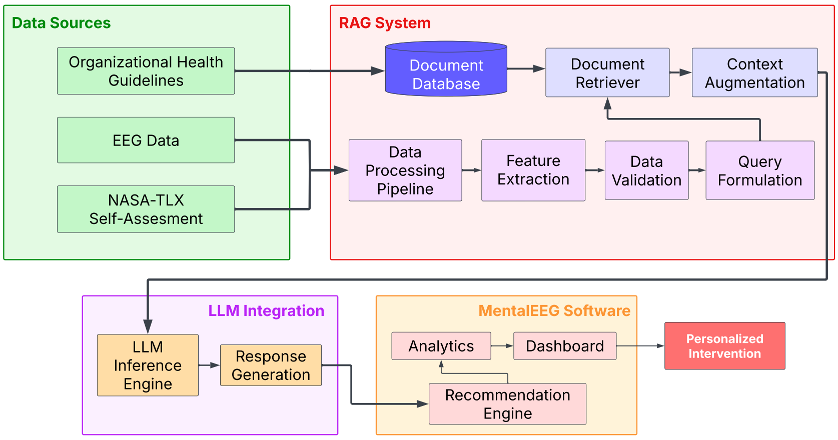

Figure 6: Integration of LLM in MWL monitoring system.

MentalEEG employs the OpenAI API to merge EEG and NASA-TLX data, delivering personalized, policy-aligned interventions (Figure 6). Using Retrieval Augmented Generation (RAG) [24, 11], it generates real-time recommendations mentioned in table 5, surpassing traditional mental health tools [8, 18]. The dashboard equips HR with visualizations for proactive workload management, enhancing mHealth solutions in preventing overload [20, 8].

Table 5
Recommendations for Mental Workload and Burnout Management from [25]

Timeframe	MWL Level	Recommendations
Short-term	2	Mobile/online stress management therapies Gamification mechanics to enhance connection with employees
Mid-term	3	Personalized health recommendation systems
Long-term	4	Involvement of professional coaches

7.2. Practical Implications and Study Limitations

MentalEEG enables real-time monitoring across individual, departmental, and organizational levels, empowering managers and HR to prevent burnout. The OpenAI API ensures personalized interventions aligned with health policies [11], while RAG contextualizes recommendations [8]. This reduces absenteeism, enhances productivity, and promotes healthier workplaces, contributing to societal well-being and quality of life.

The DSR methodology encountered limitations, including a small participant pool, limited stakeholder diversity, and insufficient dashboard evaluation criteria. Dependence on wearable biosensors introduces cost and technical barriers [17], while self-assessments risk bias [18]. Integrating complex organizational guidelines also complicates decision-making effectiveness.

7.3. Ethical Considerations and Privacy Protection

MentalEEG prioritizes privacy and ethics through transparent consent, ethical oversight, and secure data handling for sensitive EEG data [26, 27]. Designed for well-being rather than surveillance, it offers aggregated insights to HR, ensuring fairness and transparency. Future enhancements will include privacy-preserving methods like differential privacy and federated learning.

7.4. Future Research

Future work should test MentalEEG in high-cognitive-load fields (e.g., healthcare, education) and integrate it with HR software for seamless adoption. Refining LLM use with complex policies and conducting longitudinal studies will boost scalability. Also usage of custom models will increase the privacy and security of the data. Also, Adding data sources like heart rate variability and eye tracking could enhance intervention accuracy across diverse settings.

8. Conclusion

This research presents MentalEEG, a web-based MWL monitoring system that provides data-driven, real-time solutions for high-stress environments, particularly software engineering. By integrating LLM, EEG data, and self-assessments, MentalEEG addresses key gaps in workload monitoring. Developed using an iterative Design Science Research (DSR) methodology, it evolved to meet individual and organizational needs, offering real-time insights and customized recommendations.

MentalEEG's core innovation is its LLM-driven, context-aware interventions, enhanced by RAG to align recommendations with organizational health guidelines. Unlike traditional tools like NASA-TLX, which focus on individual assessments, MentalEEG provides a scalable, organizational-level solution that transforms MWL management. Its real-time analytics and AI-powered recommendations advance workload monitoring, particularly in cognitively demanding fields.

By allowing HR professionals and managers to make data-driven decisions that improve well-being, MentalEEG fosters a healthier, more engaged workforce. On a broader scale, its adoption could potentially reduce health care costs related to stress and burnout while improving work-life balance and job satisfaction. Supporting a sustainable, mentally healthy workforce, MentalEEG ensures employees and organizations thrive in demanding professional environments.

Declaration on Generative AI

During the preparation of this work, the author(s) used Grok-3 in order to grammar and spelling check. Further, the author(s) used Midjourney for figures 2 in order to generate images. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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