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EEG-Based Cognitive Load Comparison in Construction Sensor Data Analytics

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With rising interest in innovative construction methodologies, global construction companies are actively exploring emerging sensing technologies and employing data analytics techniques to draw insights and improve their operations. While numerous educational disciplines employ Block-based Programming Interfaces to enhance domain-specific data-related inquiry and visualization skills, the construction sector has yet to fully explore this practical approach. Introducing block interfaces in construction education may overwhelm newcomers with excessive cognitive load. Past research has primarily relied on subjective measures, overlooking objective indicators for assessing cognitive responses to block interfaces' interaction elements. This study evaluates the cognitive load induced using InerSens, a Block Programming Interface designed to address authentic construction challenges in ergonomic risk assessment. Electroencephalography is utilized to measure cognitive load, and the results are compared to those of a traditional tool, Excel. Theta Power Spectral Density in the frontal brain region, an indicator of cognitive load, demonstrates that in four out of six tasks, InerSens incurs lower cognitive load than Excel. The findings of this study underscore the potential of InerSens as a viable tool in managing cognitive load efficiency, paving the way for more effective and streamlined sensor data analytics learning experiences for future construction professionals.

Key Words: Block-based Programming Interface, Cognitive Load, Sensor Data Analytics, EEG, Construction Education.

Introduction

Persistent productivity and safety concerns in construction have sparked a widespread interest in integrating sensing technologies to capitalize on data-driven project enhancements. The growing adoption emphasizes the need for construction professionals to possess sensor data analytics skills for translating raw sensor data into informed decision-making (Khalid et al., 2023). Block-based Programming Interfaces (BBPIs) have been reported as an effective means to enhance learners' data analytics skills in diverse educational domains (Bender, Dziena, & Kaiser, 2022; Rao, Bihani, & Nair, 2018). Yet, construction education falls behind in leveraging BBPIs for in-demand skill development. For instance, analytics on Inertial Measurement Unit (IMU) data offers insights into worker posture or equipment activity states (Rashid & Louis, 2019). Construction practitioners can employ this information to identify anomalies, such as workers' unusual ergonomic posture or equipment's abnormal idling state to devise task modifications and improve productivity. Infusing this experience into the learning requires directly embedding the analytics pipeline within the platform, from data cleaning to visualization, enabling students to explore and learn. However, introducing BBPIs to construction education may challenge newcomers with excessive cognitive load (CL) (Rijo-García, Segredo, & León, 2022). Cognitive Load Theory posits that an excessive burden on working memory can hinder the learning process (Sweller, 1988). Additionally, a persistent high CL, stemming from subjective task complexity can detrimentally affect attention and concentration, leading to distractions and errors (Kosch et al., 2023). To overcome these potential concerns, the programming platform to teach data analytics would need to be designed in such a way that minimizes human-computer interaction (HCI)-induced CL. While BBPIs are reported to reduce CL subjectively, the implementation of objective CL measurements (i.e., Electroencephalography or EEG) during BBPI interaction is currently lacking. This limits the understanding of how BBPIs align with users' platform interaction and associated CL. The present study seeks to address the current limitation of dependable CL evaluation in BBPIs by employing EEG during interaction with InerSens, providing a more comprehensive approach to understanding CL in construction sensor data analytics. BBPI of this study, InerSens integrates end-user programming features with technical capabilities for analyzing sensor data from construction activities. The evaluation includes comparing the CL between InerSens and the conventional platform, Excel, which is typically used for similar analytical tasks. The study, through segmented task comparison, seeks to determine how CL changes for construction students across various analytics tasks and platforms while addressing authentic construction concerns like ergonomic risk assessment with sensor data.

Background

BBPIs in Education and Current States of Evaluation

More recently, BBPIs have been explored as a means to facilitate educational interventions in the topics of domain-specific data analytics (Bender et al., 2022; Rao et al., 2018). BBPIs diverge from traditional text-based commands, replacing them with interactive blocks. This simplifies code into a more manageable set of meaningful interactive elements, rendering BBPIs a versatile choice for is particularly for non-programming students (i.e., construction). Particularly, BBPIs rely on recognition, not recall, which reduces users' CL and allows them to prevent basic errors through direct structural manipulation (Bau, Gray, Kelleher, Sheldon, & Turbak, 2017). Glas, Vielberth, Reittinger, Böhm, and Pernul (2022) introduced a BBPI into a cyber range setup, and the BBPI users reported lower CL compared to the group using textual programming. Unal and Topu (2021) reported similar findings with BBPIs, in a different learning context. However, subjective CL measures may overlook undetectable CL patterns in response to nuanced BBPI interactions, motivating the adoption of EEG in this study.

Physiological Cognitive Load Measurement

Physiological cognitive load measurements refer to the objective assessment of an individual's CL during task performance using physiological signals and reactions, such as skin conductance, heart rate, or EEG. These measurements shed light on the cognitive demands made on an individual when engaging in a particular activity. Systems with advanced computational capabilities have led to complex interactive information systems, which, in turn, can also lead to increased mental strain, stress, and the potential for inefficiency and errors among users (Kumar & Kumar, 2016). The increasing use of BBPIs in domain-specific learning underscores the importance of customization, at the same time highlighting the need for thorough content and usability assessments to ensure effective education and widespread adoption (Glas et al., 2022; Rijo-García et al., 2022). Research on non-invasive physiological measures for CL assessment is limited, and it predominantly relies on self-reported subjective measures for BBPIs. It is well known that CL can be measured from EEG signals since brain signals provide a more direct way of measuring CL as cognition takes place in the human brain itself. McMahan, Parberry, and Parsons (2015) adopted EEG to study stimulus modalities and gaming events, discovering differences in cognitive demands. High-intensity events increased EEG spectral power, showing its potential for distinguishing cognitive processes. In HCI research, Theta power is associated with cognitive and memory performance. Castro-Meneses, Kruger, and Doherty (2020) used specific EEG channels, such as Theta power in left-frontal (AF3, F3) and right-frontal (AF4, F4) scalp regions, to measure CL incurred by linguistic complexity during educational video consumption. In similar tasks related to HCI, frontal Theta powers in various locations, such as AF3, AF4, F3, F4, F7, and F8, have been interchangeably used to measure CL (Cabañero et al., 2020; Kumar & Kumar, 2016).

Methodology

In this study, a usability approach was employed to assess the CL of undergraduate construction students. Participants were assigned data analytics tasks involving simulated construction activity information to draw similar conclusions in terms of developing risk assessment charts using both Microsoft Excel and the BBPI, InerSens, as depicted in Figure 1. InerSens was developed based on Google's Blockly framework, offering an interactive block-coding platform featuring essential graphical blocks and their corresponding functions within the user interface for conducting ergonomic risk analysis (see Figure 2). EEG data from the participants was collected during their task performance to compare the CL between the Excel and InerSens conditions.

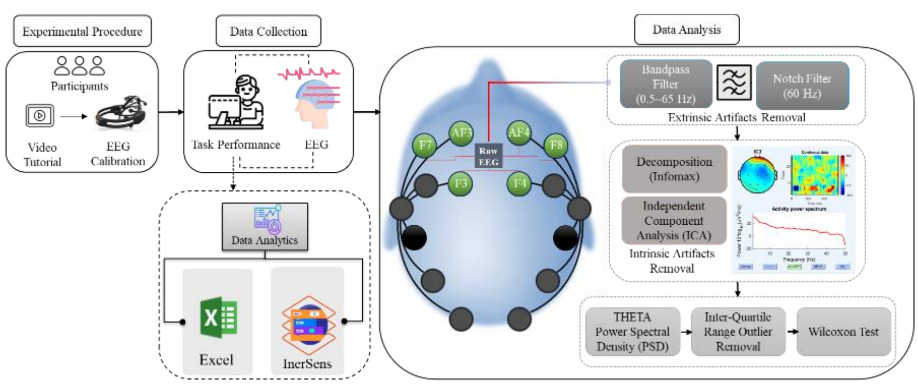

Figure 1. Research methodology overview.

Experimental Design

The study involved twenty undergraduate students majoring in building construction (BC), construction engineering management (CEM), and civil engineering (CE). The participants, with an equal gender distribution (1:1 male-to-female ratio) and a distribution of 4 students in BC, 7 in CEM, and 9 in CE, were all 18 years of age or older. Prior to the experiment, participants received tutorial materials and a 15-minute practical demonstration to become acquainted with the task procedures and platform components. Prior to recording the data, the EEG device was calibrated to ensure satisfactory signal quality. Participants undertook tasks involving interaction with pre-recorded construction activity data, including video recording and raw IMU sensor data. The six consecutive tasks on both platforms included: (a) reviewing sensor data and activity video; (b) data selection involving the choice of essential columns (e.g., timestamp and pitch); (c) manipulation and (d) defining activities, entailing the structuring of data using platform-specific formulas or functions; (e) developing risk assessment charts by utilizing the defined data; and (f) chart evaluation, which involves validating chart output against actual activity. These hands-on tasks enable students to practically analyze IMU data through a structured procedure, enhancing their grasp of analytics techniques and workplace safety in terms of construction workers' ergonomic risks.

Figure 2. InerSens interface (left) and participant (right) engaged in data analytics task.

Data Collection

Electroencephalography

EEG holds the advantage over subjective feedback in capturing brain signal variations in response to changes in cognitive stimuli and working memory load (Joseph, 2013). Moreover, it minimizes intrusion during HCI task performance, making EEG a suitable option for assessing CL during BBPI interaction. The study utilized the Emotiv EPOC-Plus, a wireless device for acquiring and processing neurophysiological EEG signals. The headset features 14 channels (AF3, AF4, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC8, F4, and F8) and 2 references (P3 and P4) following the 10-20 format, operating at a frequency of 128 Hz. Its affordability, lightweight design, and multiple channels make it suitable and effective for use in HCI settings. The brain, the hub of the central nervous system, generates electrical brain waves at various frequencies, including delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (greater than 30 Hz). Out of the 14 available channels, a subset of 6 channels was chosen for additional pre-processing. These selected channels, namely F3, F4, AF3, AF4, F7, and F8 are positioned in the frontal-mid area of the scalp and have a strong correlation with cognitive workload in HCI (Castro-Meneses et al., 2020; Kumar & Kumar, 2016).

Data Analysis

Pre-processing

The raw EEG data contains interferences, known as artifacts, which affect signal analysis. These artifacts originate externally, stemming from sources such as eye and body movements (known as intrinsic artifacts), as well as electronic interference (known as extrinsic artifacts). To eliminate these artifacts, the EEGLAB tool within MATLAB was employed with which the channels were spatially aligned to their corresponding positions and individually referenced. Extrinsic artifacts were filtered out using a bandpass filter (0.5 – 65 Hz), and a notch filter at 60 Hz was additionally applied to remove electrical noise originating from electrode wires. The filtered EEG data underwent decomposition, using the Extended Infomax method (Delorme & Makeig, 2004). This method decomposed the data into 14 components, shown on a scalp heat map indicating signal distribution percentages. After visually checking and removing unwanted components, the data was reverted to its original time-reference form. Any instances where intrinsic artifacts surpassed brain signals were eliminated through Independent Component Analysis (ICA). The spectral characteristics of the artifact-free EEG signals were computed via the Welch method. MATLAB was employed to calculate the Power Spectral Density (PSD) within the Theta frequency range for each subtask. This involved determining the magnitude of individual segments and subsequently averaging these spectral values within the 4-8 Hz frequency range for the Theta band (Cox & Fell, 2020).

Power Spectral Density, Outlier Removal, and Statistical Analysis

This study compared objective behavioral measures of CL using processed EEG data, focusing on the Theta frequency range, to evaluate differences between Excel and InerSens. Potential outliers that could impact the results were identified using Tukey's range test, which was computed using the interquartile range (IQR) (Raghu et al., 2020). Given the non-normality of the data distribution as indicated by the Shapiro-Wilk test, non-parametric Wilcoxon Signed-Ranks Tests (WSRT) were adopted using JMP Pro 2017 software. This allowed to identify if any significant differences exist between the independent variables (Excel and InerSens) with the dependent variable being the Theta PSD values for each channel. This was carried out for each of the 6 tasks. A significance threshold of $p<0.05$ was applied.

Results

This section details the results obtained from EEG measurements used to evaluate the CL of participants in both Excel and InerSens conditions. It also provides a comparative analysis of PSD values across various EEG channels for each task.

Task-based PSD Comparison

The channels located in the frontal-midline region, namely AF3, AF4, F7, F3, F4, and F8, along with their Theta PSD averages, were examined for comparison between Excel and InerSens and illustrated in Figures 3, 4, and 5. During tasks 1 and 2, it was observed that all channels exhibited higher Theta PSD values for Excel, except for the F3 channel representing the frontal left hemisphere of the brain, where InerSens demonstrated higher Theta PSD value. In task 2, for channel F7, WSRT revealed significantly higher Theta PSD values in Excel compared to InerSens. However, no other channels exhibited statistically significant differences in their Theta PSD values.

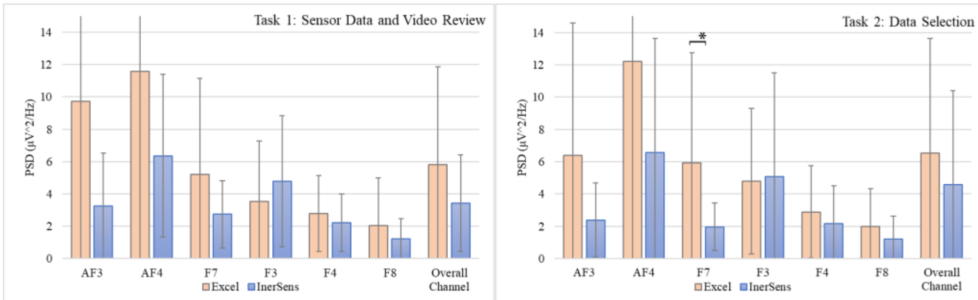

Figure 3. Comparison of Theta PSD between Excel and InerSens for tasks 1 and 2 (*signifies statistically significant difference between two conditions).

As depicted in Figure 4, during task 3, all channels, except F3, exhibited elevated PSD values in Excel when contrasted with InerSens. For task 4, all frontal channels exhibited increased Theta PSD values in Excel compared to InerSens.

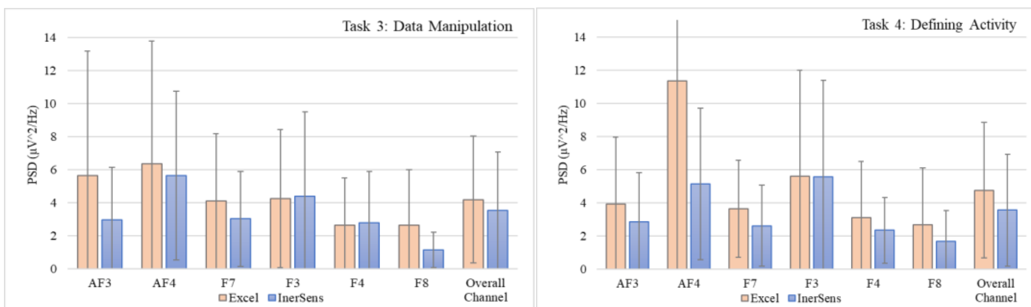

Figure 4. Comparison of Theta PSD between Excel and InerSens for tasks 3 and 4.

According to Figure 5, in task 5, a noticeable change in Theta PSD was observed, with AF4, F7, and F3 displaying higher Theta PSD values for InerSens. This resulted in a higher overall channel average for InerSens compared to Excel. In final task 6, a similar change was observed, with most channels, except for F3, showing higher Theta PSD values for InerSens in comparison to Excel. No statistical significance was observed in these differences.

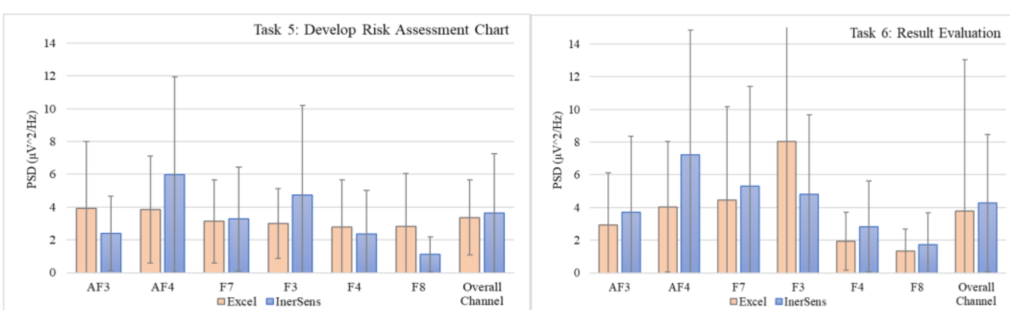

Figure 5. Comparison of Theta PSD between Excel and InerSens for tasks 5 and 6.

Overall Theta PSD Comparison

Figure 6 provides an overview of the collective average channel values of frontal Theta PSD. It shows that tasks 1, 2, 3, and 4 had higher PSD averages for Excel, while the last two tasks had higher Theta PSD for InerSens. The y-axis represents the average PSD, and the x-axis represents the tasks.

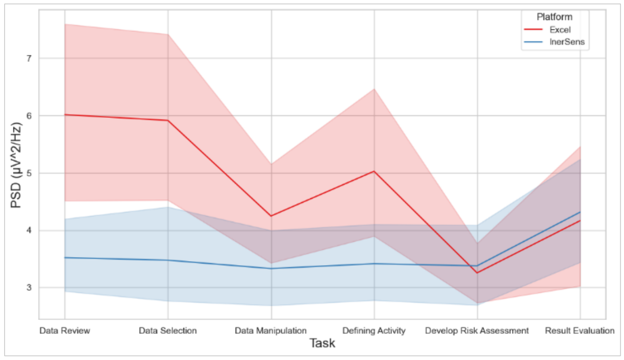

Figure 6. Comparison of average Theta PSD between Excel and InerSens for all tasks.

Discussion

The study compared CL across six tasks in Excel and InerSens conditions, finding that interaction factors, especially in specialized skill acquisition like construction sensor data analytics, can influence users' CL.In Excel condition, the tasks with the highest Theta powers were in tasks 1 and 2, where the most contributing channels were AF3 and AF4. In Excel, participants reviewed raw data, used separate video playback software, and manually searched for relevant data columns, inspecting each one individually for retention in further analysis. This task sequence, characterized by the need for a greater amount of interaction (i.e., handling large amounts of text), increases CL as indicated by Harper, Michailidou, and Stevens (2009). These activities appear to be mentally taxing, requiring divided attention across interfaces and manual data searches, align with previous research linking increased Theta power to task complexity or the number of tasks to be completed (Puma, Matton, Paubel, Raufaste, & El-Yagoubi, 2018). Such demands can impact users by increasing CL, particularly evidenced by heightened Theta power, and potentially affecting overall user experience. In contrast, InerSens used specific action blocks for these manual-natured tasks and had lower CL than Excel, indicated by lower Theta power despite AF3 and AF4 channels being the highest contributors. Task 3 in Excel involved creating columns and using formulas for data conversion, while task 4 required manual extraction and matching of timestamps. In these cases, InerSens simplified data extraction with a unified screen and interactive buttons, reducing steps and recording lower Theta power, indicating reduced CL compared to Excel. In tasks 5 and 6, InerSens showed increased Theta power in multiple channels (AF4, F7, F3, and F8), leading to a higher average frontal Theta power compared to other tasks. The cause of increased Theta power in task 5 remains unclear, but in task 6, differences in participant activities can be attributed to the distinct functionalities of the platforms they used. In Excel, participants could only view a static risk assessment chart, while InerSens offered a dynamic, real-time chart synchronized with the activity video. This dynamic chart showed changing colors in response to the subject's range of motions, leading to longer interaction times and more clicks to explore the results. Although visually more complex, this aligns with research by Brasell (1987) indicating that real-time sensor data graphing enhances learning. Excel lacked the ability to provide such real-time visualization, likely explaining the differences in interaction and cognitive demand during the final task of chart evaluation. Although InerSens had higher CL in some tasks, overall CL was greater for Excel based on EEG data. Only task 2 showed a significant difference in the F7 channel with Excel having higher PSD than InerSens, but the limited sample size (n = 20) may not detect statistical significance for small differences for other channels. This study's results support existing literature indicating that BBPIs help reduce CL for users. The outcomes also emphasize that extraneous CL is influenced by both design and integrated learning environment interactions, going beyond content and multimedia presentation. While elevated CL may lead to errors, reducing it can improve system effectiveness. Therefore, utilizing EEG for tracking CL provides a more reliable measure in evaluating educational software, ensuring optimal content complexity, and improving learning and retention.

Conclusions and Future Work

In summary, the findings of this study indicate that EEG analysis can effectively discern the engagement of cognitive resources, specifically reflected in the changes of Theta rhythm within the frontal region of brain activity. Furthermore, the research highlights the substantial impact of BBPI's design characteristics on users' brain activity, particularly in terms of power spectral measurements. This study demonstrates that construction students can leverage BBPIs to facilitate their introduction to the field of sensor data analytics, as evidenced by the reduced CL observed in this condition compared to the traditional alternative, Excel. The speed of information flow, the complexity of information visualization, and the pressure associated with decision-making can collectively contribute to a high CL for users, potentially resulting in errors or even disengagement. Therefore, effective monitoring and evaluation of users' CL in complex HCI systems hold significant significance, as it can enhance system interactivity and promote higher acceptance within the educational community. It is essential to acknowledge that, despite efforts to identify distinctive characteristics for each task type, the specific nature of the task remains a significant determinant of CL. Additionally, the study's utilization of a small sample size (n=20) may constrain the generalizability of the results to a broader population or different demographic groups. Future work will involve a larger sample size and utilize users' prior knowledge, experience, and skills to investigate potential CL variations stemming from individual differences.

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