PREDICTION OF COGNITIVE LOAD DURING INDUSTRY-ACADEMIA COLLABORATION VIA A WEB PLATFORM

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ABSTRACT*: Web platforms are increasingly being used to connect communities, including construction industry and academia. Design features of such platforms could impose excessive cognitive workload thereby impacting the use of the platform. This is a crucial consideration especially for new web platforms to secure users' interest in continuous usage. Understanding users' cognitive workloads while using web platforms could help make necessary modifications and adapt the features to users' preferences. Users' usage patterns can be leveraged to predict the needs of users. Hence, the pattern of cognitive demand that users experience can be used to predict the cognitive load of web platform users. This could provide insights, generate feedback, and identify areas of modification that are critical for sustaining acceptability of web platforms. Using recurrent neural network, this study adopts electroencephalogram (EEG) data as a physiological measure of brain activity to predict brain signals (cognitive load) of users while interacting with a web platform designed to connect industry and academia for future workforce development. This paper presents a Long Short-Term Memory (LSTM) based approach to develop a model for predicting users' cognitive load via EEG signals. Nineteen (19) potential end-users of the proposed web platform were recruited as participants in this study. The participants interacted with the web-platform in a real case scenario and their brain signals were captured using a five-channel EEG device. The validity of the proposed method was evaluated using root mean square error (RMSE), coefficient of determination (R^2), and comparison of the predicted and actual EEG signals and mental workload. The results revealed the reliability of the model and provided a suitable method for predicting users brain signals while using web platforms. This could be leveraged to understand users' cognitive demand which could provide insights for web platform improvements to engender users' continuous usage.*

KEYWORDS: *Cognitive load, electroencephalogram, industry-academia collaboration, long short-term memory, web platform.*

1 INTRODUCTION

To achieve a balanced blend of theory and practice, as well as adequately prepare students for a rapidly changing industry like the construction sector, collaboration between industry and academia is important. Academia differs from the industry in that the industry is known for practical application of knowledge while academia is known for teaching and research. These differences are complementary in preparing the future workforce for the workplace. Therefore, this necessitates a connection between instructors and practitioners for collaborations in future workforce development. However, there are myriads of challenges plaguing these collaborations of which a prime challenge is instructors' access to practitioners (Chandrasekaran, Littlefair, & Stojcevski, 2015). Since the outbreak of Covid-19, the internet is being increasingly used to connect individuals and communities, for example, to connect instructors to students, and buyers to sellers. The usage of the internet has been growing over the decades, with a transition from mere information sharing medium to workspaces, marketplaces, and even communities (H.-F. Lin, 2009; Schmutz, Heinz, Métrailler, & Opwis, 2009; Wellman, 2004). Dale, Basumatary, Iqbal, Khullar, and Shaikh (2022) used Facebook to connect diverse community users to archived language collections. Maher, Oropello, Roman, and Zeoli (2022) also showed how the internet was used to connect underserved communities to increase health care access and improve care outcomes. Internet-based technologies have also been leveraged to build virtual communities (H.-F. Lin, 2009). Therefore, a web-based platform could be used to connect instructors to different practitioners who are willing and able to provide complementary input in course offerings. Hence, a web-based platform was designed to give instructors improved access to practitioners who could provide complementary inputs in instructors' pedagogical effort and support the preparation of students for the industry. However, during interaction with web-based platforms, there is a risk of cognitive overload. Cognitive overload is an indicator of non-intuitive interface, poor presentation of information which requires more efforts to interact with thereby exhausting cognitive resources. Therefore, to ensure that the web platform for connecting instructors with practitioners has little or minimal downsides, it is important to ensure it has minimal cognitive demand on users.

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High cognitive load has been identified as an indication of web usability problem (Albers, 2011) but this is not always the case. Users' performance and success in the use of web-based platforms depends not only on the web platform but also on users. This is because human cognitive resources at a point in time are limited, unstable, and vary from person to person. Also, the perceived cognitive demand for the same activities varies among people (Das, Chatterjee, & Sinha, 2013), for example due to differences in prior knowledge (Seufert, Jänen, & Brünken, 2007), users skill level (Kumar & Kumar, 2016), and amount of cognitive resources available (Tracy & Albers, 2006). In addition, regardless of intrinsic features of a web-based platform that could impact users' cognitive load, other extrinsic factors such as lack of adequate sleep, temporal demand, and stress (Tracy & Albers, 2006) could reduce the amount of cognitive resources available to users at a point in time. Therefore, due to these varying and fluctuating extrinsic factors, a user can experience different levels of cognitive demand on the same web-based platform at different times even when the platform is not changing. Majority of prior studies (Hewitt & He, 2022; F.-R. Lin & Kao, 2018; Mills et al., 2017; Schmutz et al., 2009) focused on detection of cognitive load and the impact of web-platforms' intrinsic characteristics on users' cognitive load with little or no attention on extrinsic factors that are user-dependent which also impact cognitive demand. This represents a major limitation to the generalizability of user experience on the same web platform due to the fluctuation and differences in human cognitive resources. This also accounts for disparities between usability evaluations and real-world scenarios which usually skewed the results of several user testing research. Hence, one-size-fits all approaches cannot meet users' unique and differing needs.

Therefore, to address the dynamism in web-platform usage because of the varying and unstable nature of cognitive resources, adaptive and personalized website design would be beneficial (Desai, 2021). To achieve this, (Adomavicius & Tuzhilin, 2005) recommended leveraging usage patterns to predict the needs of users. A reliable prediction of cognitive load is a fundamental step toward adaptive design (Appel et al., 2019). Hence, the pattern of cognitive demand that users experience can be used to predict the cognitive load of users. This could also help to generate feedback and identify areas of modification that are critical for sustaining acceptability of web platforms. In addition to subjective measures (e.g., NASA TLX), electroencephalogram (EEG) is a growing objective measure of cognitive load in human computer interaction. This has been used by previous studies (Caldiroli et al., 2023; Kumar & Kumar, 2016) to assess cognitive load in web-platform usage. Previous studies (Appel et al., 2019; Herbig et al., 2020) have focused on predicting cognitive load with other physiological measures (such as eye tracking metrics, heart rates, and galvanic skin response) using machine learning. Most previous studies (Caldiroli et al., 2023; F.-R. Lin & Kao, 2018; Mills et al., 2017) focused on using EEG to detect cognitive load in web platform usage. Only a few studies such as (Friedman, Fekete, Gal, & Shriki, 2019; Mills et al., 2017; Yoo, Kim, & Hong, 2023) used EEG for prediction of cognitive load in web platform usage. Mills et al. (2017) leveraged EEG spectral features using partial least squares regression to develop a model to predict cognitive load during interactions with an intelligent tutoring system. Yoo et al. (2023) developed a long short-term memory (LSTM)-based machine learning model to predict the degree of cognitive load using EEG data. The study showed that LSTM had the highest accuracy of 87.1% compared to random forest (64%), AdaBoost (64.31%), support vector machine (60.9%), XGBoost (67.3%), and artificial neural network models (71.4%). Using EEG data for prediction of cognitive load, Friedman et al. (2019) assessed different machine learning predictive models and reported that XGBoost has the highest predictive power compared to random forest, artificial neural network, and simple linear regression models. Therefore, if a web platform is held constant over time, users' cognitive demand can be predicted with EEG signals as they interact with the platform. Hence, this study leverages EEG signals to develop a model for predicting the cognitive demand of a web platform designed for industry-academia collaborations. The results of predicting users' cognitive load could help identify patterns in the usage of the platform which could inform necessary modifications to ensure optimum usability that could influence users' acceptance and intention to use the proposed web-based platform

2 BACKGROUND

The success of new information systems hinged on users' acceptance (Davis, 1985). However, high cognitive load could affect user's satisfaction as well as acceptance of a new web-platform. For example, high cognitive load is an indication of web usability problems (Albers, 2011). Hu, Hu, and Fang (2017) demonstrated that cognitive load can affect user satisfaction with a website. This could affect users' revisit, trust, and loyalty (Desai, 2021). Hewitt and He (2022) showed that difficulty of task to be performed and web page contrast could impact users' cognitive demand and perceived usability. Schmutz, Roth, Seckler, and Opwis (2010) revealed that mode of presentation of information on web platforms impacts users' perceived cognitive load. Examples of other problems associated with web-based platforms which could affect the cognitive load of users include confusing link name or description, horizontal scrolling, and atypical interface design which negate users' mental model (Albers, 2011). The cognitive demand of web-based platforms is crucial because human cognitive resources are limited. Hence, there is a risk of web-platforms requiring more cognitive resources than what users possess, which results in cognitive overload (Albers, 2011). Despite design principles, users of web platforms could be overwhelmed or confused because of information overload and/or excessive obstacles to overcome before locating the right information. Cognitive overload could interfere with mental processing of information which could cause users to exit a web page or even fail to locate appropriate content (Albers, 2011). Other manifestations/impact of cognitive overload on web users include task shedding, increase in frustration, multiple mistakes, lack of attention to detail and disregard of content (Albers, 2011; Kumar & Kumar, 2016). As cognitive demand increases, users' performance plummets (Tracy & Albers, 2006). Hence, the need to assess cognitive load of users as they interact with web-based platforms.

Though originated from psychology, assessment of cognitive load has translated into physiological sensing where objective measures such as EEG are increasingly being used to complement subjective measures (Kumar & Kumar, 2016). The limitations of subjective measures (such as bias and inability to currently recall actual experience or perception) make objective measures (e.g., EEG) growing methods for assessing cognitive load. Through electrodes on the scalp, EEG collects brain signals resulting from cognitive processes taking place in the brain (Kumar & Kumar, 2016). These signals vary depending on the type of activities in the brain and correspond to cognitive load (Mills et al., 2017). By leveraging deep learning techniques, EEG signals can be used to predict cognitive load via real time data from brain signals. Prior studies have demonstrated the efficacy of EEG to predict the cognitive load in different contexts (Moghar & Hamiche, 2020; Salman, Heryadi, Abdurahman, & Suparta, 2018; Yoo et al., 2023) using Recurrent Neural Networks (RNN). RNN are deep learning techniques commonly used for time series forecasting of sequential data (Qin & Bulbul, 2023). However, major downsides of RNN include the time intensive nature of traditional RNN and difficulty in training the models because they are prone to vanishing and exploding gradient problems (Van Houdt, Mosquera, & Nápoles, 2020). To circumvent this challenge, advanced architectures like LSTM are being used in diverse contexts to develop prediction models for time series. For example, in prediction of mental workload during construction task using augmented reality head mounted display (Qin & Bulbul, 2023), stock market prediction (Moghar & Hamiche, 2020), and weather forecasting (Salman et al., 2018). LSTM consists of input layer, output layer and an intermediary LSTM layer (or hidden layer) (Moghar & Hamiche, 2020). The input layer receives data as input, while the output layer determines data that will be output. The hidden layer is made up of memory cells and three gates that are in charge of updating the cell state. LSTM is a gradient-based method used for capturing long-term dependencies in sequential data (Hua et al., 2019). The primary component of LSTM that enabled this capability of LSTM is the memory block (Van Houdt et al., 2020). Memory block (or LSTM cell) is a subnetwork comprising a memory cell (also known as cell state) and three gates (namely, input gate, output gate and forget gate) (Staudemeyer & Morris, 2019). The memory cell retains the temporal state of the neural network while the gates control the flow of information. The input gate manages the inflow of new information into the memory cell using Equation 2 and 3 and updates the memory cell by Equation 4. The amount of existing information which remains in the current memory cell is controlled by the forget gate as illustrated in Equation 1. The output gate regulates the amount of information for computing the output activation of the memory block and how it propagates to the rest of the neural network (Hua et al., 2019) using equations 5 and 6. The structure of the LSTM cell is shown in Figure 1.

$$f_t = \sigma(W_f\,[h_{t-1}, x_t] + b_f) \quad \text{...Eqn. 1}$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad \text{...Eqn. 2}$$
$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad \text{...Eqn. 3}$$
$$c_t = ft \odot c_{t-1} + it \odot \tilde{c}_t \quad \text{...Eqn. 4}$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad \text{...Eqn. 5}$$
$$h_t = ot \odot \tanh(c_t) \quad \text{...Eqn. 6}$$

Weight matrices for the forget gate, input gate, cell state and output gate are denoted by W_f, W_i, W_c, W_o. In the same order, b_f, b_i, b_c, b_o represent the bias vectors. Elementwise (Hadamard) multiplication is denoted by $\odot$, logistic sigmoid function by σ, and the hyperbolic tangent function by tanh. h_t and c_t represent the hidden state and cell state at time t respectively.

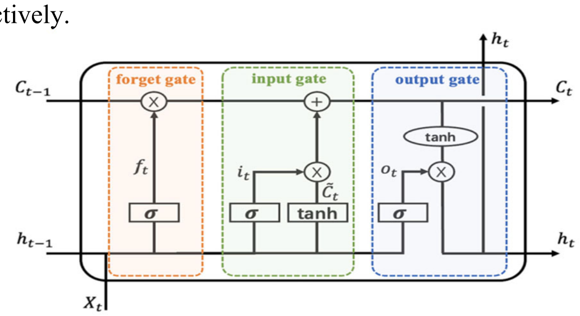

Fig. 1: Architecture of LSTM network.

Mental workload can be estimated from spectral power which represents the brain rhythm's energy (Qin & Bulbul, 2023). A positive relationship existed between cognitive load and theta rhythm power, whereas a negative relationship exist between cognitive load and alpha rhythm power (Gevins, Smith, McEvoy, & Yu, 1997). Hence mental workload can be calculated using equation 7 similar to Qin and Bulbul (2023).

$$\mathrm{MW(t)} = \frac{\theta f\,(\mathrm{t})}{\alpha\, p(\mathrm{t})} \quad \text{......Eqn. 7}$$

MW(t) represents the mental workload at time t; θf(t) and αp(t) are the mean spectral power of theta and alpha rhythm at time t respectively.

3 METHODOLOGY

3.1 Overview of the Web Platform

The web platform in this study is designed to be a collaborative network of instructors and practitioners for future workforce development. The aim of the platform is to improve instructors' access to practitioners who could provide practical supplementary inputs in construction engineering education to aid students' preparedness for the industry. The potential users of the platform are instructors in construction-related programs (such as Building Construction, Architecture, Civil and Environmental Engineering as well as Construction Engineering and Management) and construction industry professionals. The platform was designed by leveraging participatory design, interaction design and user-centered-design principles (Freire, Arezes, & Campos, 2012). Users' input and participation in the design process were ensured through usage research. Usage research was used to elicit pertinent information from end users. The information elicited served as inputs for the design of optimal graphic user interface of the platform. By leveraging heuristics design principles for user interface design (Nielsen, 1994), the platform was designed to be typical to other platforms that potential users are familiar with. This is to ensure that the platform operational procedure is similar to users' mental mode which could enhance ease of use of the platform as well as users' acceptance. To use the platform, an instructor is required to sign up, verify email address, complete profile, submit request for course-support, view recommended practitioners from the platform and select preferred practitioner to meet the course-support request. The course-support requests include site visits, guest lectures, seminars, workshops, and other activities that allow students to interact with practitioners under the guidance of an instructor. The platform was designed using JavaScript programming language. A relational database management system (MariaDB) was adopted with Node.js as server.

3.2 Experimental Design

After a brief introduction of the platform to participants. The procedure of the experiment was explained. All participants provided their informed consent by signing the consent form. The participants interacted with the web-based platform. Each participant was required to sign up on the platform. Thereafter, participants verified their email address before first login. Upon login, the participants were required to complete their profile after which they requested a course-support from practitioners. After a request for course-support, participants viewed recommended practitioners to meet their course support request. Out of these recommendations, instructors made a selection. Every session of the experiment was conducted under similar conditions.

3.3 Participant and Study Approval

Nineteen (19) participants were recruited after the research protocol was approved by the Virginia Tech Institutional Review Board. The participants include both male and female professors (the proposed end-user of the web-based platform) with varying degrees of experience, different job titles and from diverse construction-related academic programs such as civil and environmental engineering, building construction, architecture, and construction engineering and management.

3.4 Data Collection

As participants use the web-based platform, their cognitive load was objectively measured via braai signals using an electroencephalogram (EEG) device called EMOTIV Insight. EMOTIV Insight has five channels, namely AF3, AF4, T7, T8, Pz with semi-dry polymer sensors and two reference sensors (CMS and DRL). The channels are arranged according to the 10/20 international EEG system. EMOTIV Insight has a sampling rate of 128 samples per second per channel for EEG signal with frequency response of 0.5-43Hz, digital notch filters at 50Hz and 60Hz. The device has Bluetooth connectivity which can be connected to a computer or mobile device with Bluetooth V5.0. EMOTIV Insight provides coverage of the frontal, temporal and parietal lobes which are associated with cognitive effort (Kumar & Kumar, 2016). The EEG recording was about ten (10) minutes on average per participant. An overview of the methodology is shown in Figure 2.

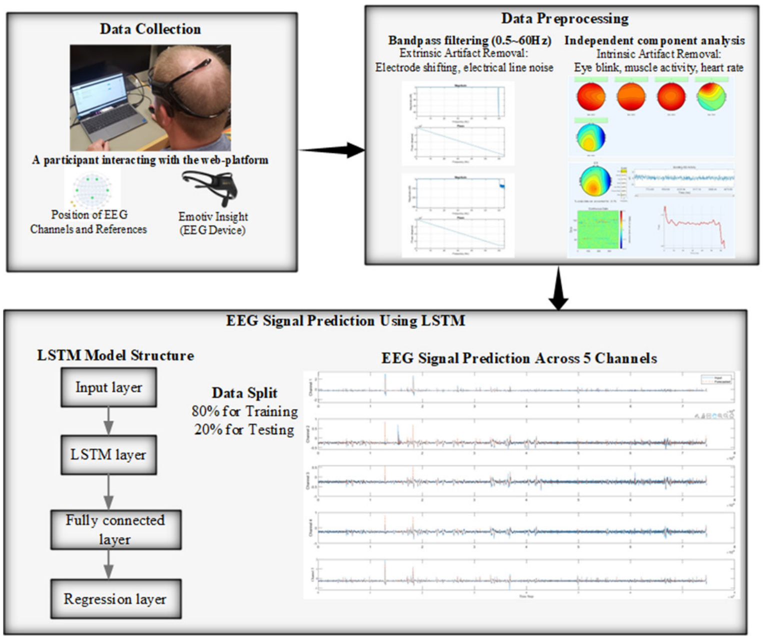

Fig. 2: Overview of methodology.

3.5 Data Preprocessing and Analysis

The raw EEG data collected with the EmotivPRO app was cleaned. Thereafter, the processes highlighted below were carried out.

3.5.1 Artifacts removal

EEG signals are susceptible to diverse categories of artifacts which represent noise/interferences to signals of interest. These artifacts are either intrinsic or extrinsic. Intrinsic artifacts are generated by EEG user's body movement such as blinking and muscle activity. Extrinsic artifacts originate from external factors such as shifting of electrode, noise from electrode wiring and surroundings noise (Jebelli, Hwang, & Lee, 2018). According to Urigüen and Garcia-Zapirain (2015), these artifacts are usually small when the EEG device is used in a somewhat stationary position as it was in this study. Both intrinsic and extrinsic artifact removals were done using EEGLAB. The cleaned EEG data in CSV format were converted to MATLAB file and imported into EEGLAB. The data was mapped and structured using 5-channel location. The extrinsic artifacts were removed using basic band pass filter range of 0.5Hz to 60Hz. As recommended by Delorme and Makeig (2004), Extended Infomax method was used to decompose the EEG data through independent component analysis (ICA). The data was decomposed into 5 components, displayed with scalp heat maps and intrinsic artifacts were rejected.

3.5.2 Data Processing

Five (5) brain wave frequency bands were captured by each of the five (5) electrodes of the EEG device (EMOTIV Insight) used in this study. These frequency bands include Theta (4-8Hz), Alpha (8-12Hz), Low Beta (12-16Hz), High Beta (16-25Hz), Gamma (25-45Hz). The cleaned data for all the nineteen participants from the five (5) channels of the EEG device were used for the analysis. There were 79936 data points on average for each participant for an average recording time of 10 minutes. The data points were split into 80% and 20% for training and testing respectively.

3.5.3 Prediction framework

The preprocessed EEG data was used to train the LSTM network for prediction of EEG signals. Open loop forecasting was adopted because true values of brain signals (representing cognitive load) from EEG were used to train the LSTM network for prediction. Similar to Kingma & Ba (2014), Adaptive Moment Estimation which is an extension of the stochastic gradient descent algorithm was used for optimization with a learning rate of 0.001.

To ensure that the loss is as small as possible an epoch of 250 was adopted for training the model. Root Mean Square Error (RMSE) was used to calculate the loss function to determine the performance of the model. The LSTM layer has 128 hidden units or memory cells to capture and store information over time, which enables the LSTM network to process sequential data effectively. The hidden units determine the amount of information learned by the layer. Both the sequence input layer and the fully connected layer of the LSTM regression neural network have sizes that match the number of channels of the input data.

3.5.4 Mental workload

Because it is not possible to directly measure mental workload from EEG signals, the signals were converted into frequency domain. This conversion enabled the calculation of the average spectral power of particular brain rhythms, hence, the Power Spectral Density (PSD) of the signal was calculated. PSD is a measure of the mean power distribution of a signal over a specific timeframe with the unit showing energy per frequency (Qin & Bulbul, 2023). The mental workload was estimated using equation 7 for both the actual and predicted EEG signals.

4 RESULTS AND DISCUSSION

4.1 Performance Evaluation

The performance of the predictive model was evaluated using RMSE. The RMSE shows the difference between the predicted and actual values of the EEG signals. Table 1 shows the RMSE for all the test participants. The average of the RMSE was 0.0674. The RMSE of the test participants' datasets were very low (<0.037) except for the third participants whose RMSE was 0.1607 which skewed the average of the RMSE to 0.0674. However, the low RMSE of the other test participants' datasets reveal the high predictive power of the LSTM model by indicating marginal difference between the actual and predicted EEG signals. This agrees with Miyamoto, Tanaka, and Nakamura (2022) who posited that the closer RMSE is to zero the better. The high RMSE of the third participant in the test dataset could be attributed to insufficient data points. All other participants had more than 74,000 data points while the third participant had about 58,500 data points amounting to a difference of 16,000 data points. Also, the EEG recording time of the participant was very short and fell below the average duration. This agrees with Pyo et al. (2018) who opined that low RMSE might be because of insufficient data points. In addition, although 58,500 data points seem considerably high, this result reveals that prediction models require large amounts of data for accurate forecasting. This position is also supported by Ettinger et al. (2021), even though there are no fixed number of data points required for predictive models. However, considering other factors such as complexity of problem, desired performance and complexity of model, this result could provide a guide for future research.

Table 1: RMSE for test participants.

Test Participants	1	2	3	4
RMSE	0.0356	0.0367	0.1607	0.0367

The performance of the LSTM prediction model was further assessed as shown in Figure 3 by comparing the predicted and actual EEG signals of the test dataset for the five (5) EEG channels. The comparison reveals that the predicted EEG signals follow a very similar pattern as the actual EEG signals. Although there were minor deviations where the path of the predicted signals did not align with the actual EEG signals, to a large extent, the model was able to accurately predict sudden and subtle fluctuations. However, it appears that the model was able to predict subtle fluctuations better than sudden drastic changes in the EEG signals. Overall, the predictive model can be adjudged reliable especially in predicting subtle fluctuations in the EEG signal. To further show the performance (validity) of the predictive model, scatter plot was used to plot the predicted values and the actual values of the test data set for each EEG channel (see Figure 4).

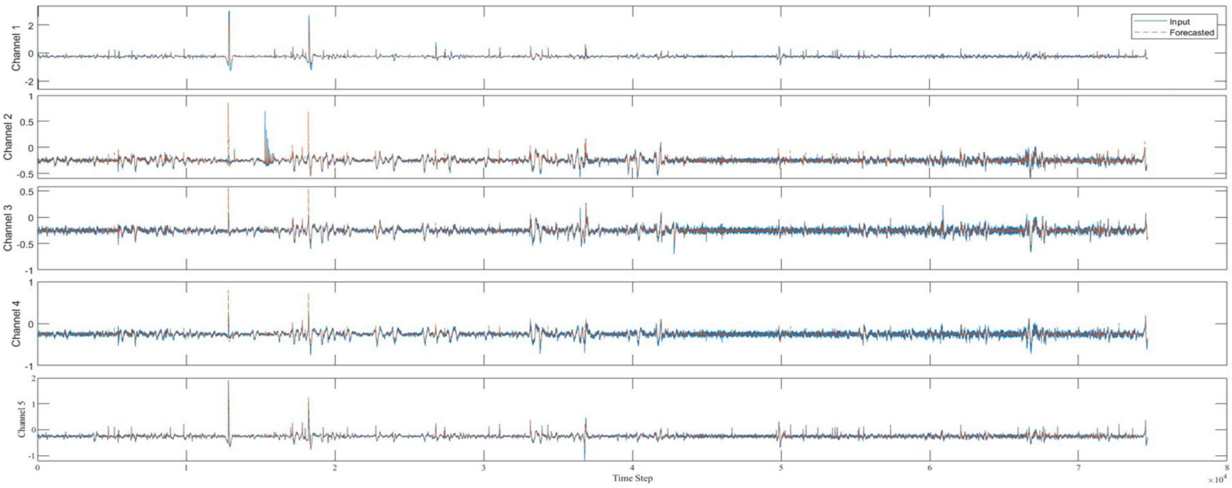

Fig. 3: Comparison of predicted and actual EEG signals for the test dataset across the five EEG channels.

The scatter plots in Figure 4 and the R^2 in Table 2 show that the model was able to explain a significant proportion of the variability in the actual EEG values. R^2 is the coefficient of determination which indicates the goodness-of-fit of the regression model. Given the low RMSE for the test participants and the high R^2 for the channels, it is evident that the model captured the underlying pattern in the data effectively, and the predicted values are very close to the actual values. The model could therefore be considered accurate because as Alexander, Tropsha, and Winkler (2015) explained, RMSE is a useful indicator of a model's practical value. The high R^2 values show that a significant portion of the underlying patterns and relationships in the actual data is accounted for by the predictions made by the LSTM model. This is because according to Chicco, Warrens, and Jurman (2021), RMSE is a measure of the average errors between predicted values and actual values while R^2 explains the amount of variance in the data that the model could explain. Hence, the overall value of a model has been defined by its accuracy and precision and as well as by its effectiveness in elucidating the variability in datasets (Coulibaly & Baldwin, 2005; Qin & Bulbul, 2023). Also, given that the low RMSE values were for the test participants while the high R^2 values were for the EEG channels, it is shown that on the overall for a participant, the model was able to achieve little error between the actual EEG signals and the predicted EEG signals, and for each EEG channel, the model was able to explain a significant portion of the variability in the data for prediction. Hence, the model is able to give reliable prediction of participants' EEG signals.

Table 2: R^2 for each channel.

Channel	AF3	T7	PZ	T8	AF4
R^2	0.9336	0.7683	0.8022	0.7541	0.8854

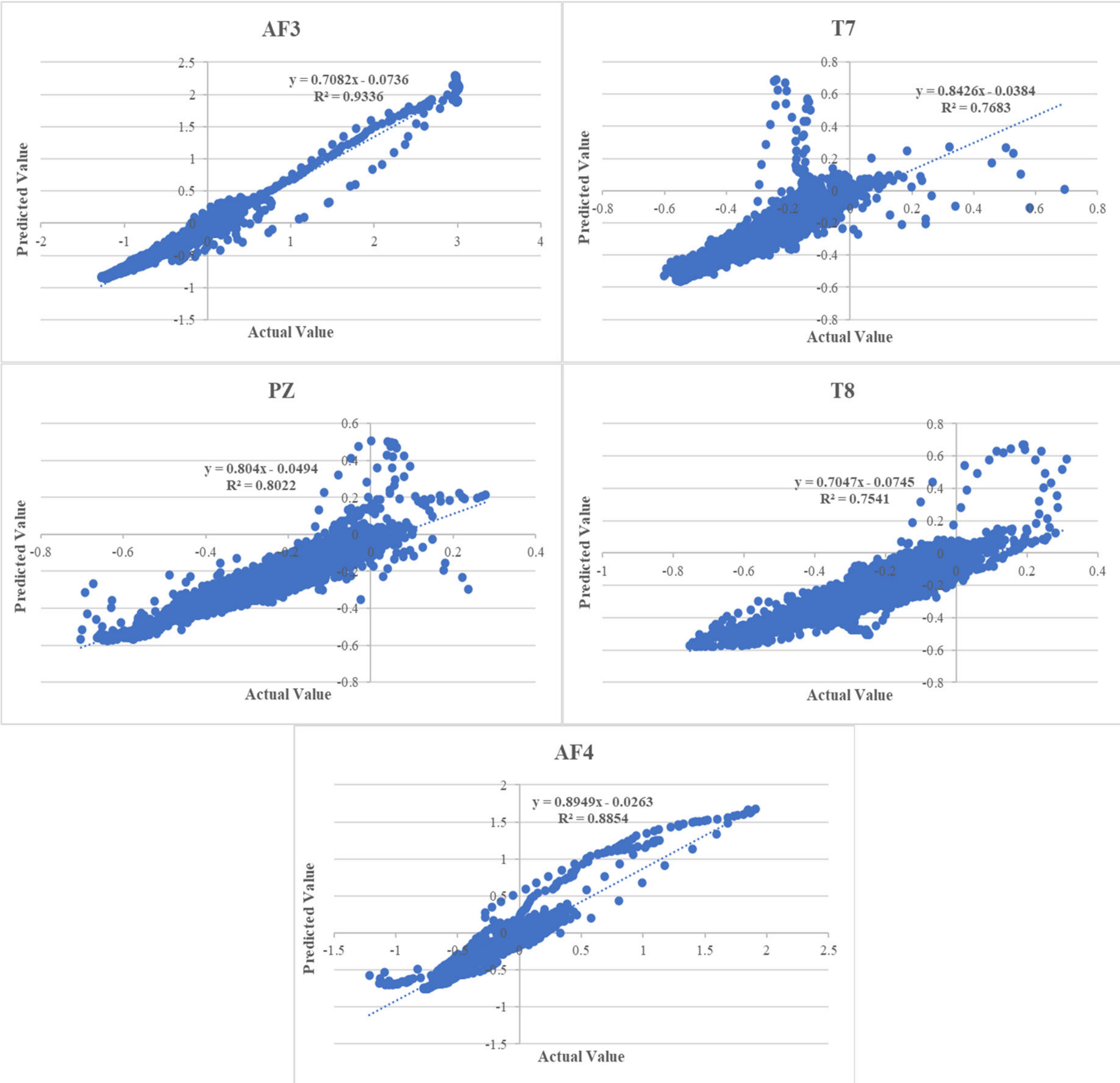

Fig. 4: Scatter plots showing the predicted and actual values for the 5 EEG channels.

As shown in Table 2, the R^2 values are ≥ 0.7541. Channel AF3 has the highest R^2 value, this is followed by channel AF4, PZ, T7 and T8 respectively. The scatter plots show the linear relationship between the predicted and actual EEG signals. Although as shown in Figure 4, there are few data points that deviated from the linear relationship in each EEG channel, a great proportion of both the predicted and actual EEG values fit into the linear relationship. For example, the lowest R^2 value is 0.7541 shows that about 75.41% of variance in the actual EEG signals is accounted for by the predicted signals. According to Coulibaly and Baldwin (2005), R^2 values in the range of 0.8 - 0.9 are considered acceptable and those > 0.90 are considered very satisfactory. Only three EEG channels (AF4, PZ and AF4) fall within this range. However, as revealed by Alexander et al. (2015), RMSE is a more informative indicator of a model's usefulness compared to R^2. This is because, the value of a model should be based on its accuracy and precision and not on its explanatory power of variability in a particular data set (Alexander et al., 2015). Chicco et al. (2021) also noted that R^2 value can be quite low even when dealing with a fully linear model, and the opposite is also true. Therefore, overall, the results show that brain activity of users using a web-based platform can be reliably predicted with EEG signals.

4.2 Mental Workload

Figure 5 shows the scatter plot of the predicted mental workload plotted against the actual mental workload. According to Coulibaly and Baldwin (2005), the R^2 value (> 0.90) was very satisfactory. This shows that the predicted mental workload matches the actual mental workload which further reinforces the efficacy of the LSTM model to learn and predict the cognitive load of users during industry industry-academia collaboration via a web platform. The results reveal that 92.50% of the variance in the actual mental workload can be explained by the predicted mental workload. This provides a reliable prediction of mental workload of users in industry-academia collaboration via a web platform. This potential of LSTM model to predicted cognitive load has been corroborated by earlier studies such as Salman et al. (2018) and Qin and Bulbul (2023).

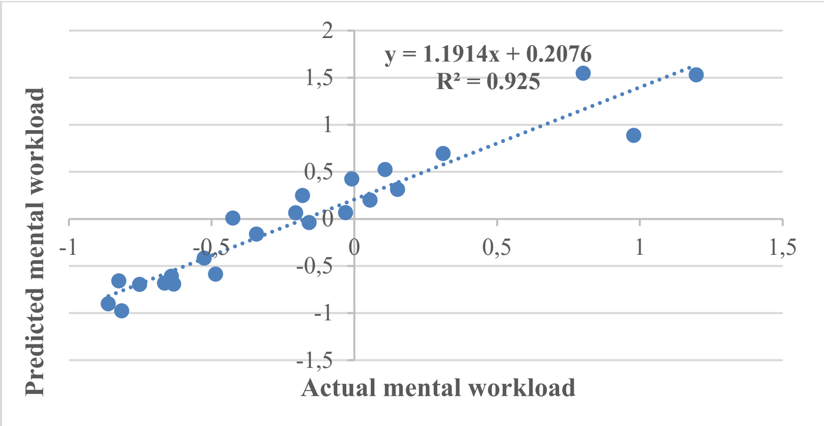

Fig. 5: Relationship between actual and predicted mental workload.

5 CONCLUSION, LIMITATIONS AND FUTURE WORK

Cognitive load is a major consideration in the design and usage of user interfaces because it could influence users' attitude towards the web platform as well as continual usage. Through web platforms, the internet is being leveraged to connect instructors in construction-related programs with construction industry practitioners who could support their pedagogical efforts in preparing students for the workplace. Using LSTM, this study assessed the effectiveness of EEG-based prediction of brain signals (representing cognitive load) as instructors interact with the web platform designed to connect them with practitioners. The results demonstrated the accuracy and reliability of the LSTM model to predict EEG signals as users interact with the web platform. The model was able to predict subtle fluctuations better than sudden drastic changes in the EEG signals. The results showed low RMSE and high R^2 values which indicate that the model's predictions are close to the actual values, and it is explaining much of the variability in the data. The efficacy of the model to predict EEG signals could be leveraged to understand users' pattern of cognitive demand in human-computer interaction. This pattern of users' cognitive demand could provide a better understanding of the cognitive resources expended by users as they interact with the web platform. This is critical because users' cognitive resources and cognitive demand varies due to both intrinsic and extrinsic factors hence a one-time detection of cognitive load might not provide adequate insights. The prediction of EEG signals could be used to understand users' usage patterns and necessary modifications required to enhance interface functionality, navigation, content integration as well as user experience. This is crucial for new web platforms which users are unfamiliar with and which could operate differently from their mental model. Also, the process of users' acclimatization with the platform as well as the impact of learning curve in using the web platform could be better understood through the prediction model. The study has some limitations which should be acknowledged. Although the sample size is adjudged adequate, using a higher sample size could yield better results. Also, LSTM was used in this study, future work could focus on using different network models for comparison of accuracy and reliability. Future work could likewise explore achieving lower RMSE and higher R^2.

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