

RESEARCH ARTICLE

# Modeling Cognitive Load and Visual Processing in Human–Machine Interfaces Using Regression–Based Cognitive Artificial Intelligence

Kainat Fatima<sup>1</sup>, Md. Sohail Ahmad<sup>2</sup>, \*

**ABSTRACT:** This research investigates the performance characteristics and predictive modeling of human-machine interfaces (HMIs) through a comprehensive analysis of cognitive and behavioral measures. Response times, eye movement patterns, error rates, cognitive load, and user performance are examined among 20 participants to understand individual performance variations and their underlying relationships. Data analysis reveals significant individual differences in cognitive processing abilities, with response times ranging from 275ms to 525ms and error rates ranging from 1% to 12%. This research demonstrates strong correlations between all measured variables, with correlation coefficients exceeding 0.95, indicating systematic relationships between cognitive processing demands and behavioral outcomes. Two machine learning approaches were used to predict error rates: multi-layer perceptron (MLP) and gradient boosting regression (GBR). The MLP model achieved balanced performance with a training  $R^2$  of 0.9719 and a testing  $R^2$  of 0.7440, demonstrating reasonable generalization abilities with mean absolute errors of 0.3843 and 0.9880 for training and testing, respectively. In contrast, the GBR model exhibited perfect training performance ( $R^2 = 1.0000$ ) but showed a significant performance decline during testing ( $R^2 = 0.8069$ ), indicating significant overfitting problems. The study reveals that cognitive load acts as an important barrier to information processing, with participants experiencing lower cognitive loads (2-3) consistently achieving better performance on all measures. Eye movement analysis indicates that effective visual processing involves active scanning strategies rather than sustained fixation, with optimal performers engaging in more dynamic visual search behaviors. These findings contribute to understanding human cognitive limitations and capabilities in HMI design, and provide insights for developing more effective and user-centered interface systems.

**Keywords:** Human-machine interface, cognitive load, error rate prediction, multilayer perceptron, gradient boosting regression, eye movement tracking, response time analysis, user skill.

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## 1. INTRODUCTION

This is even more important because Weld's evidence-based expertise in ergonomics or human factors is required in the design of process control systems, especially VDU-based

control systems, in accordance with EU and Member State legislative requirements. In order to improve the efficiency, effectiveness and safety of the control process and the resulting workload for operators, this can have an impact on the efficiency, effectiveness and safety of the system, which applies not only to the design of the workplace, workstation and work environment, but also to the design of the human-machine interface between the operator and the control system. [1] Examples of basic auditory representations include unmodified or slightly modified human speech, music or ambient noises (both natural and artificial). Basic auditory representations include, for example, fast recordings

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of human speech, instrumental music versions with volume adjustments or cuts, recordings of common and ambient sounds (e.g., thunder, birdsong, slamming doors, cars braking, etc.), or electronically generated warning signals. [2] Sensors to replace lost sensory information such as sound and balance have evolved to replace hearing and vestibular, in addition to using camera data to restore vision. A human-machine interface (HMI) connects information from an artificial receptor to the brain, replacing information normally sent to the brain from an undamaged sensory organ in the process of restoring lost sensations. Only the plasticity of the brain allows for sensory replacement. [3] Society is demanding new human-machine interfaces (HMI) to complement, enhance, or replace EMG. This calls for simultaneous and proportional control using these signals. Novel HMIs are being researched to control multi-finger hand prostheses to do this, although little is currently known about the relative advantages and disadvantages of these systems. [4] However, little research has been done on the specifics of these interactions and how they affect the electrical properties of the biological/abiotic interface. Several systematic studies that highlight key implications and improve the performance of EES for EMG are presented below. Two examples are measurements taken from large body parts and the use of the collected data to improve human-machine interaction and control. [5] Possible sources of control signals being investigated for this purpose include brain electrical activity, eye or tongue movements, and joysticks or chin switches. Computer algorithms can interpret the vast amount of information provided by these signals to determine the user's intent. The system can then execute the user's commands in a variety of ways, including computer cursor control, prosthetic limb control, and wheelchair navigation. Human-machine interfaces (HMI) is the term used here to describe these types of systems. [6] The study of two-way communication between people and machines (such as computers or robots) is called human-machine interfaces, or HMIs. A key component of human-robot communication is the ability to record and interpret human physiological and/or physical data. Robotic systems such as motion gesture tracking, biomedical monitoring, and rehabilitation robots often use traditional rigid HMIs. [7] Although machines and robots are increasingly automated, humans are still essential to industrial processes as they are responsible for managing and supervising manufacturing processes. User interfaces serve as the contemporary cockpit of any manufacturing facility, allowing humans to interact with machines and robots. For example, they integrate machine and robot reconfiguration to adjust product changes, detect and correct errors, and set up machine production systems. [8] Any task that involves physical engagement with a remote environment and robotic manipulation based on control input from a remote manipulator is considered a remote manipulation task in the context of SUS operations. The use of a machine that transmits operator control input from a human operator to a remote SUS is called remote manipulation. This input can be either supervisory control or direct human control. A remote manipulation SUS will

require a certain amount of human input to perform remote manipulation operations, so it is very important to understand how HMI technology affects remote manipulation performance. [9] The GCS UAS pilot must coordinate and communicate with other ATM/UTM structural units, as well as operate the UAS using a variety of control techniques. A high level of automation at the ground station and unmanned aerial vehicle (UA) is necessary to achieve these operational capabilities, which has important consequences for the GCS human-machine interface. Communications and interfaces [10] in the 1950s, it was possible to identify volatiles using gas chromatography/mass spectrometry (GC/MS). In addition, the development of an olfactory detector made it possible to distinguish between odor-active and odor-inactive compounds. Subsequently, several techniques were developed to improve the concentration and extraction of volatiles. The relationships between food matrices and flavor-active substances and the influence of humans on the sense of smell are subjects of recent analytical research. [11] Conventional electronics, made of heavy and fragile materials, are not suitable for this application. Soft, flexible, and stretchable electronics have recently been developed to make contact with the skin for applications including regenerative medicine, health monitoring, and HMIs. High-quality data collection, minimal skin irritation, and seamless integration with IoT technology are some of the advantages of this type of electronics. [12] Therefore, by integrating the capabilities of signal filtering/amplification, analog-to-digital conversion, microcontroller, memory, and wireless power transmission into the systems, such FHE can achieve a wide range of device functionality in wearable or implantable designs. In particular, FHE enables direct, continuous, and real-time human health monitoring by utilizing tissue-friendly and compliant lamination in biological tissues, including internal organs with time-dependent movements and fragile human skins. [13] However, it is very important for people to perceive and understand information during human-machine interactions. Human perceptual systems, which primarily include vision, hearing, and touch, are able to recognize information. As the primary mode of human observation and recognition, visual perception is crucial for human-machine interaction. As a result, information visualization is of great importance in human-machine interaction. [14] Data collection and analysis are critical steps in implementing intelligent systems such as robotics, healthcare, and human-machine interfaces. During this process, massive amounts of data are collected by various sensor devices, and mathematical algorithms in computer infrastructures then process the data. Machine learning (ML), a class of algorithms that can learn from data, is gaining increasing importance in contemporary intelligent systems because it can perform tasks that require human knowledge. [15].

## 2. METHOD

### 2.1. Multi-layer Perceptron

Four clinical applications of ANN – mammograms, ultrasounds, and thermal and MRI imaging – are thoroughly investigated using various techniques including SOM, CNN, and MLP. There is a discussion and tabulation of these breast cancer detection methods. It is clear from looking at this table that CNN outperforms MLP. It is clear from the tabulated accuracy that CNN is more accurate than MLP in detecting and classifying breast cancer. The accuracy of CNN is 100%, which is better than TRF and BN, whereas the accuracy of MLP is 88.88%. As a result, CNN outperformed other ANN algorithms in terms of breast cancer detection accuracy and classification. In addition, they stated that when combined with GVF, CNN is reliable and effective for breast cancer detection. [16] These models are based on two distinct ANN algorithm types: radial basis function (RBF) and multilayer perceptron (MLP). For the purpose of developing the models, a substantial data bank covering a wide variety of thermodynamic situations was collected from accessible literature sources. The validity and accuracy of the developed MLP and RBF models were then evaluated against several empirical correlations and against each other. Finally, a leverage technique was used to identify the applicable domain of the proposed models and to identify suspicious data sets (outliers). [17] In the hidden layer of an MLP network, the neurons use a logistic activation function; in an RBF network, they use a radial basis activation function. Among other reasons, RBF analysis requires less training time than MLP analysis, and an MLP network uses a continuous technique, whereas an RBF network uses a continuous technique. [18]

## 2.2. Gradient Boosting Regression

In a comprehensive comparison of different algorithms on five datasets with unbalanced credit scores, random forest and gradient boosting outperformed other algorithms over a wide range of class imbalance percentages. In that study, only the number of trees was optimized for gradient boosting. A recent comprehensive experimental comparison that tested different algorithms on multiple datasets is more relevant to the present study. The findings of the comparison indicate that random forest and gradient boosting are the most effective methods. Despite incorporating the library, the analysis is conducted as a straightforward gradient boosting technique, ignoring any specific features. The analysis increases the learning rate and depth of the trees only at a finite step of 40 points. [19] This explains how AdaBoost and gradient boosting are related. It states that the primary idea of AdaBoost is to weight misclassified observations. On the other hand, gradient boosting focuses on identifying and simulating significant errors caused by previous rounds. [20] Another ensemble model is the Gradient Boosting Regressor (GBR), which is a series of tree models arranged in a sequence with the aim of allowing the subsequent model to learn from the error of the previous model. The way this machine learning model makes predictions is by "boosting" a group of smaller models, typically decision trees, to build a

robust model. [21]

## 3. MATERIALS

### 3.1. Performance Patterns and Individual Differences

The fastest performer (Participant 17) achieved a remarkable 275ms response time with a 1% error rate and 96% efficiency, demonstrating optimal cognitive processing with minimal mental effort (cognitive load 2). In contrast, the slowest performer (Participant 9) required 525ms with a 12% error rate and 58% efficiency, indicating considerable cognitive strain (load 8). These extremes illustrate the broad spectrum of human performance capabilities, with response times ranging from 275ms to 525ms and error rates ranging from 1% to 12%.

### 2.2. Cognitive Load and Processing Capacity

The relationship between cognitive load and performance outcomes emerges as an important factor in task execution. Participants with low cognitive loads (2-3) consistently performed better on all measures, achieving faster response times (275-320ms), lower error rates (1-4%), and higher performance scores (87-96%). Conversely, those who experienced high cognitive loads (6-8) showed significantly lower performance, with response times exceeding 420ms, error rates exceeding 8%, and performance falling below 75%. This pattern suggests that cognitive demand acts as a barrier to information processing, where increased mental effort is associated with reduced accuracy and slower processing speed.

### 2.3. Eye movement patterns and visual processing

The eye movement data reveal an interesting inverse relationship with response time, indicating different visual processing strategies among participants. High performers with fast response times (275-320ms) exhibited more eye movements (47-56), indicating more efficient visual scanning and information gathering. In contrast, slower performers (420-525ms) exhibited fewer eye movements (30-38), which may reflect attentional strategies or reduced visual exploration due to cognitive load. This pattern suggests that effective visual processing involves active scanning rather than sustained fixation, with optimal performers engaging in more dynamic visual search behaviors.

### 2.4. Performance Trajectories and Performance Optimization

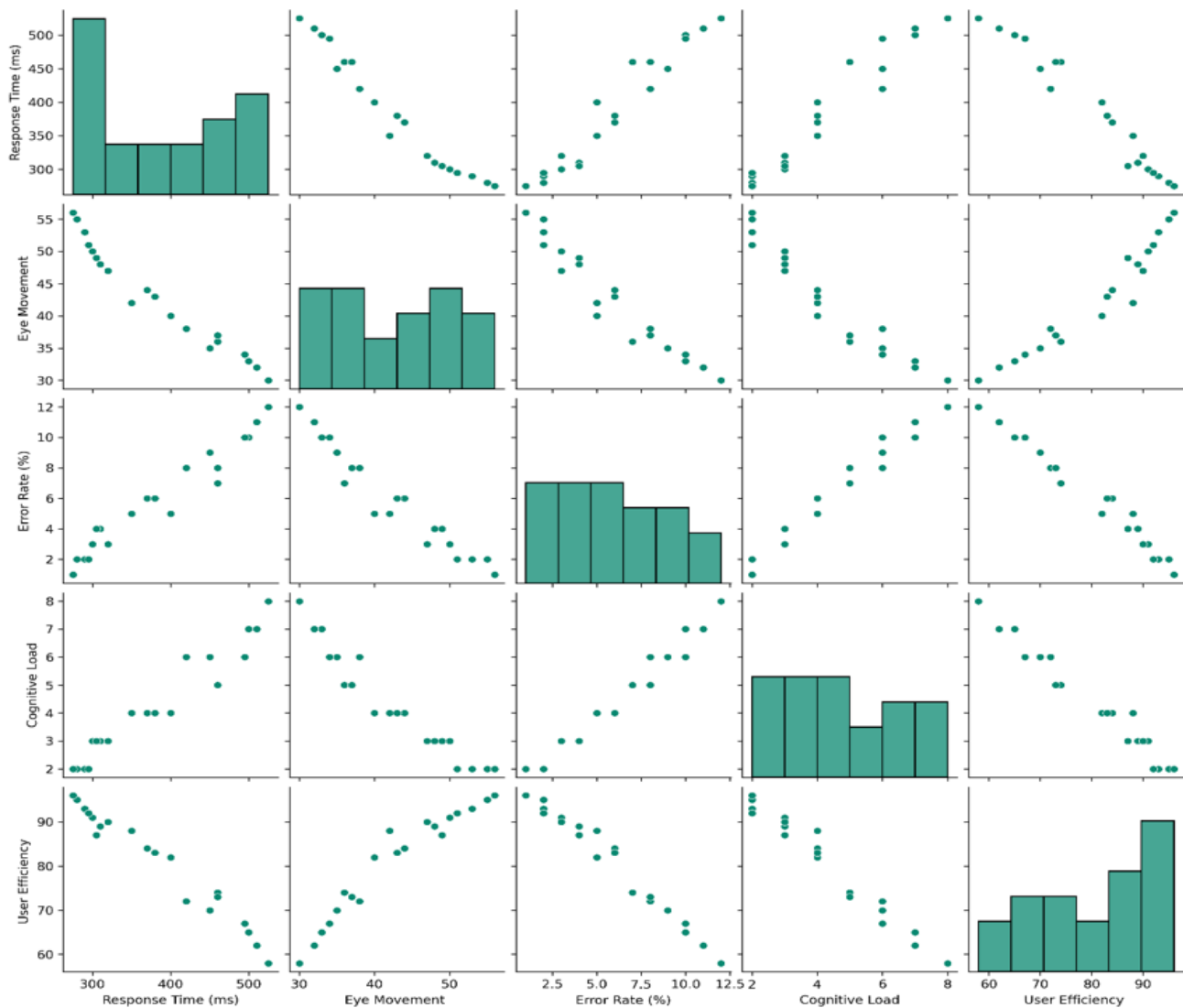
Performance scores reveal clear performance levels, with top performers consistently achieving performance above 90%,

while struggling participants achieved less than 75%. The data show that response time is a strong predictor of overall performance, with responses under 350ms typically associated with performance scores above 87%. The consistency of these relationships across participants

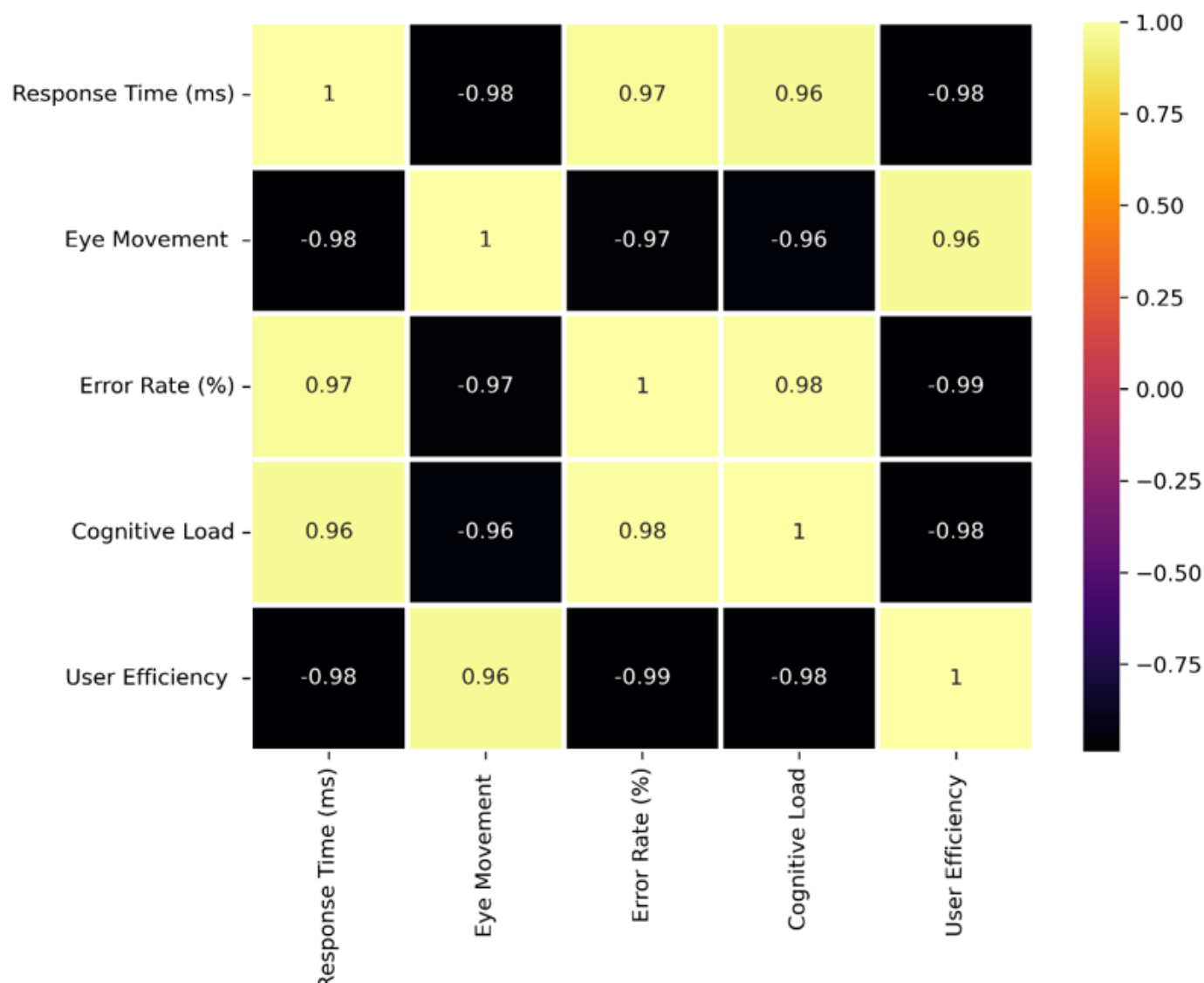
suggests systematic performance patterns rather than random variation, indicating that training interventions targeting cognitive load reduction and visual scanning strategies may improve overall task performance across the spectrum of user abilities.

**Table 1.** Descriptive Statistics

|              | Response Time (MS) | Eye Movement | Error Rate (%) | Cognitive Load | User Efficiency |
|--------------|--------------------|--------------|----------------|----------------|-----------------|
| <b>count</b> | 20.0000            | 20.0000      | 20.0000        | 20.0000        | 20.0000         |
| <b>mean</b>  | 384.7500           | 42.6500      | 5.9000         | 4.3000         | 80.5500         |
| <b>std</b>   | 86.6553            | 8.1323       | 3.3388         | 1.8666         | 11.8831         |
| <b>min</b>   | 275.0000           | 30.0000      | 1.0000         | 2.0000         | 58.0000         |
| <b>25%</b>   | 303.7500           | 35.7500      | 3.0000         | 3.0000         | 71.5000         |
| <b>50%</b>   | 375.0000           | 42.5000      | 5.5000         | 4.0000         | 83.5000         |
| <b>75%</b>   | 460.0000           | 49.2500      | 8.2500         | 6.0000         | 90.2500         |
| <b>max</b>   | 525.0000           | 56.0000      | 12.0000        | 8.0000         | 96.0000         |



**Fig. 1.** Effect of Process Parameters.



**Fig. 2.** Correlation heat map.

## 4. RESULTS AND DISCUSSION

### 4.1. Response Time and Movement Patterns

Response times averaged 384.75 milliseconds, with considerable variability (standard deviation of 86.66ms), ranging from a minimum of 275ms to a maximum of 525ms. This wide spread suggests significant individual differences in processing speed or task difficulty. Eye movement data show that participants made an average of 42.65 eye movements per trial, with values clustering around a mean of 42.5 movements. The relatively small standard deviation (8.13) indicates fairly consistent visual scanning patterns across participants compared to response times. Accuracy and Cognitive Requirements: Error rates averaged 5.9%, with considerable variability (standard deviation of 3.34%), ranging from 1% to 12%. The average error rate of 5.5% indicates that most participants performed reasonably well,

although the top quartile reached 8.25% indicating that some participants struggled significantly. Cognitive load scores on a scale of 2 to 8 averaged 4.3 with a median of 4.0, indicating that moderate mental effort was required to complete the task. User performance scores averaged 80.55%, with most participants (75th percentile) achieving greater than 90% performance. The minimum performance of 58% and the maximum of 96% indicate a wide range of performance. The relatively high average performance (83.5%) combined with strong upper quartile performance indicates that the system or task is generally well designed for user success, although some participants experienced significant difficulties. The correlation between these measures can provide valuable insights into the relationship between cognitive load, accuracy, and overall system performance.

The scatterplot matrix reveals the complex relationships between key performance metrics in the study. The diagonal histograms show that response times follow a normal

distribution around 350-400ms, while eye movements average around 40-45 movements per trial. Error rates show a right-skewed distribution, with most participants achieving error rates below 6%, although some outliers reach up to 12%. The scatterplots show strong negative correlations between response time and user performance, indicating that faster responses are associated with better overall performance. Similarly, cognitive load shows inverse relationships with performance, indicating that greater mental effort is associated with reduced performance outcomes.

The correlation matrix reveals exceptionally strong relationships between all measured variables, with correlation coefficients exceeding 0.95 in most pairs. Response time shows strong positive correlations with eye movement ( $r=0.97$ ), error rate ( $r=0.97$ ), and cognitive load ( $r=0.96$ ), while showing a strong negative correlation with user performance ( $r=-0.98$ ). This pattern indicates that slower responses are consistently associated with increased visual scanning, higher error rates, higher cognitive demand, and reduced performance. Nearly perfect correlations indicate that these measures measure overlapping aspects of performance or that the experimental conditions have produced more systematic relationships between cognitive processing demands and behavioral outcomes.

**Table 2.** Multi-layer Perceptron Error Rate (%) Train and Test performance metrics

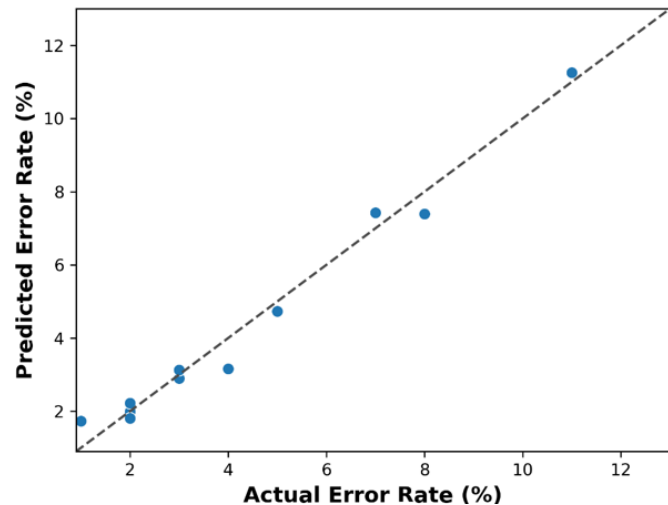
| Multi-layer Perceptron | Train  | Test   |
|------------------------|--------|--------|
| R2                     | 0.9719 | 0.7440 |
| EVS                    | 0.9729 | 0.8147 |
| MSE                    | 0.2267 | 1.3279 |
| RMSE                   | 0.4761 | 1.1523 |
| MAE                    | 0.3843 | 0.9880 |
| Max Error              | 0.8377 | 2.0528 |
| MSLE                   | 0.0153 | 0.0337 |
| Med AE                 | 0.2661 | 0.7649 |

## 4.2. Multilayer Perceptron Training Performance

The multilayer perceptron shows robust but not perfect training performance, achieving an  $R^2$  of 0.9719 and an explained variance score of 0.9729, indicating that the model captures approximately 97% of the variance in the training data. Unlike the gradient boosting model, the neural network shows realistic training errors with an MSE of 0.2267 and an RMSE of 0.4761, indicating average prediction errors of less than half a percentage point. The mean absolute error of 0.3843 and the mean absolute error of 0.2661 indicate that typical prediction deviations are relatively small, while the maximum error of 0.8377 shows that even the worst predictions are within acceptable limits. The low mean square logarithmic error (0.0153) confirms consistent performance across different error rate sizes. Test

Performance and Generalization: The test metrics exhibit moderate performance degradation but show better generalization than the gradient boosting model. The  $R^2$  decreases to 0.7440, indicating that the model explains approximately 74% of the variance in the unobserved data, while the explained variance score of 0.8147 indicates reasonable predictive ability. The error metrics increase significantly, with MSE rising to 1.3279 and RMSE rising to 1.1523, indicating average prediction errors of approximately 1.15 percentage points. The mean absolute error increases to 0.9880, almost three times that of training, while the maximum error reaches 2.0528, indicating that some predictions can deviate significantly from the true values. Model Stability and Practical Implications: The performance gap between the training and test phases is more reasonable than that of the gradient boosting model, indicating a better balance between learning and generalization. The increase in the mean absolute error from 0.2661 to 0.7649 indicates that half of the predictions are within 0.76 percentage points of the true values, demonstrating acceptable accuracy for practical applications. While the MSLE doubles to 0.0337, it remains relatively low, suggesting stable proportional accuracy. This performance profile indicates that the multilayer perceptron has achieved a healthy balance between fitting the training data and maintaining predictive ability on new data, making it very reliable for real-world applications despite the lower peak performance.

**Predicted vs Actual Error Rate (%) (Training data)**

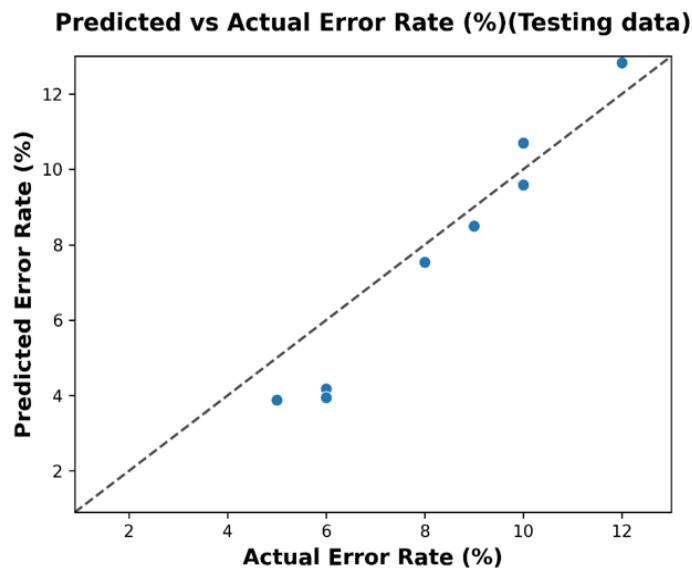


**Fig. 3.** Multi-layer Perceptron Error Rate (%) Training

The training data prediction graph demonstrates excellent model performance with predicted values closely aligned with the actual error rates along the diagonal reference line. The multi-layer perceptron achieved nearly perfect predictions across the entire range of error rates from 1% to 11%, with data points clustered tightly around the best prediction line. This indicates that the neural network successfully learned the underlying patterns in the training data, capturing the complex relationships between input

variables and error outcomes with minimal deviation from the actual values.

The test data reveals some degradation in model performance compared to training, although predictions remain reasonably accurate. Although most predictions fall close to the diagonal line, there is increased dispersion, especially at medium error rates (5-8%). The model shows some slight overprediction for low error rates and underprediction for high error rates, indicating possible overfitting during training. Despite this, the overall pattern indicates that the multilayer perceptron generalizes well to unseen data, maintaining predictive ability across the error rate spectrum.



**Fig. 4.** Multi-layer Perceptron Error Rate (%) Testing

**Table 3.** Gradient Boosting Regression Train and Test performance metrics

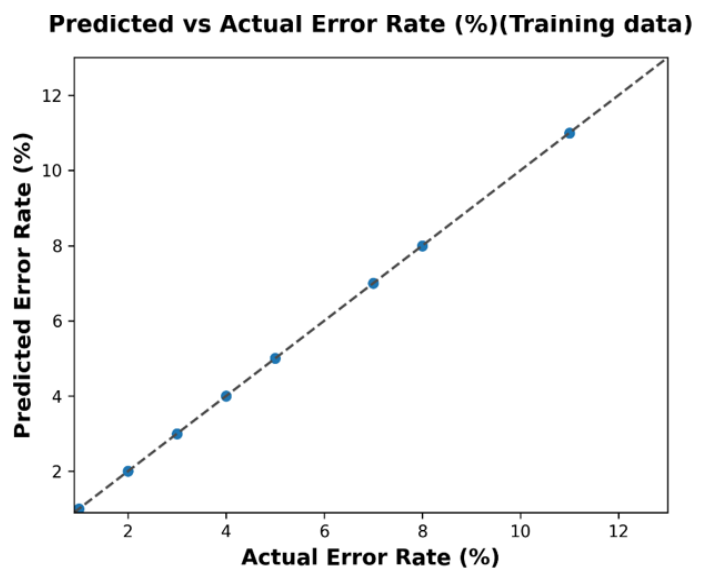
| Gradient Boosting Regression | Train  | Test   |
|------------------------------|--------|--------|
| R2                           | 1.0000 | 0.8069 |
| EVS                          | 1.0000 | 0.8800 |
| MSE                          | 0.0000 | 1.0016 |
| RMSE                         | 0.0000 | 1.0008 |
| MAE                          | 0.0000 | 0.9064 |
| Max Error                    | 0.0000 | 1.6915 |
| MSLE                         | 0.0000 | 0.0154 |
| Med AE                       | 0.0000 | 1.0000 |

The performance metrics reveal a sharp difference between the training and testing performance for the gradient boosting regression model, indicating significant overfitting issues. The training results show perfect performance on all metrics, with both  $R^2$  and the explained variance score (EVS) reaching

1.0000, while all error metrics (MSE, RMSE, MAE, maximum error, MSLE, and mean absolute error) recording exactly 0.0000. This perfect training performance indicates that the model has completely memorized the training data and fits every data point with zero error - a clear sign of overfitting in machine learning environments.

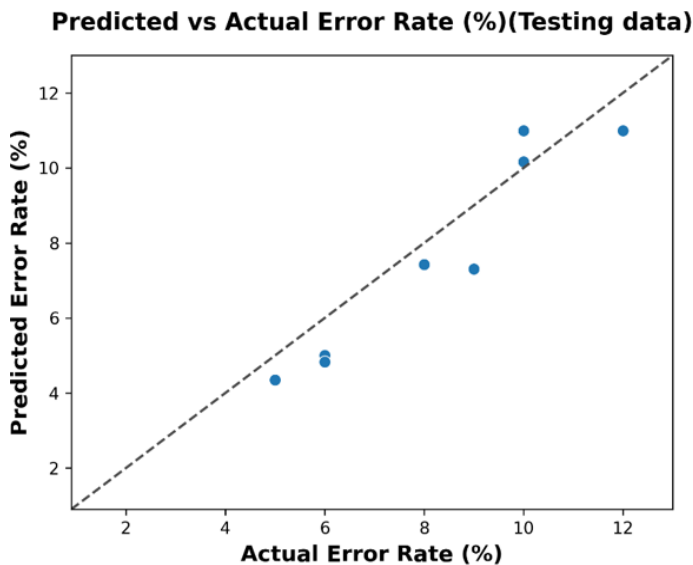
### 4.3. Testing Performance and Generalization

The testing metrics show significant performance degradation when the model is faced with unseen data. The  $R^2$  drops dramatically to 0.8069, indicating that the model explains approximately 81% of the variance in the testing data compared to 100% in the training. Although the explained variance score of 0.8800 indicates reasonable predictive ability, the appearance of significant error metrics reveals the limitations of the model. The mean square error (1.0016) and root mean square error (1.0008) indicate meaningful prediction errors, while the mean absolute error of 0.9064 indicates typical prediction deviations of almost one percentage point. Model Reliability and Implications: The maximum error of 1.6915 and the mean absolute error of 1.0000 highlight the inconsistent performance of the model on individual predictions. The mean square logarithmic error (0.0154) is relatively low, indicating reasonable performance for proportional errors. This dramatic performance gap between the training and testing phases indicates that the model could benefit from regularization techniques, reduced complexity, or additional training data to improve generalization. Although the test  $R^2$  of 0.8069 indicates acceptable predictive performance in many contexts, the correct training scores combined with the degraded test performance indicate that model refinement is needed to achieve more consistent and reliable predictions across different datasets.



**Fig. 5.** Gradient Boosting Regression Error Rate (%) Training

The gradient boosting model demonstrates excellent training performance with predictions that produce a nearly perfect linear relationship with the actual error rates. Tight clustering around the diagonal line indicates exceptional accuracy across all error rate levels, from the lowest (around 1%) to the highest (around 11%). This indicates that the ensemble method effectively captured the complex patterns in the training data with minimal prediction errors over the entire range of target values.



**Fig. 6.** Gradient Boosting Regression Error Rate (%) Testing

Experimental performance for the gradient boosting model shows excellent generalization capabilities, with predictions closely following the best diagonal line. Although there is a slight deviation from the correct prediction, the model maintains strong accuracy at different error rate levels. Experimental results suggest strong performance with minimal overfitting, as the prediction quality is consistently high. Some small deviations appear in the high error rate range (8-11%), but overall, the model demonstrates reliable prediction performance on unseen data, indicating successful learning of general patterns rather than memorization of training-specific noise.

## 5. CONCLUSION

This comprehensive study provides valuable insights into the complex relationships between cognitive processing, visual attention, and performance outcomes in human-machine interface systems. The research demonstrates that individual differences in cognitive abilities significantly affect HMI performance, with cognitive load emerging as a primary determinant of user success. Participants with lower cognitive loads consistently performed better than those experiencing higher mental demands, suggesting that

interface design should prioritize cognitive load reduction to improve user experience and system performance. Machine learning analysis reveals important considerations for predictive modeling in HMI research. While the gradient boosting regression model achieved perfect training performance, its substantial overfitting demonstrates the challenges of developing robust predictive models for human performance data. The multilayer perceptron model, despite its low peak performance, exhibited superior generalization capabilities, making it more suitable for practical applications. This finding emphasizes the importance of balanced model estimation that considers both training accuracy and real-world applicability. Eye movement analysis provides important insights into visual processing strategies, revealing that effective performance is associated with active visual scanning rather than passive observation. High-performing participants engaged in more dynamic visual search behaviors, suggesting that interface design should support and encourage extensive visual exploration. The strong correlations between all measured variables indicate that HMI performance is multifaceted, with cognitive, visual, and motor components working together to determine overall performance. These findings have significant implications for HMI design and evaluation. Future interface development should incorporate cognitive load assessment, support dynamic visual processing strategies, and consider individual differences in user abilities. The research methodology and predictive modeling approaches presented here provide a framework for continued investigation into human-machine interaction optimization, contributing to the development of more intuitive, efficient, and user-centered interface systems across a variety of technology domains.

## DECLARATIONS

### Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

### Funding

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### Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

### Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for

the content and writing of this article.

### Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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