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Effectiveness of a Multifunction Virtual Keyboard with Electrooculography Signals for People with Disabilities

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ABSTRACT

People with motor and speech disabilities often face difficulties in using digital communication tools and controlling electronic devices, limiting their independence. Although electrooculography (EOG)-based human-computer interaction (HCI) systems have achieved high accuracy in specific tasks, most remain fragmented and task-specific, restricting their real-world applicability. This study proposes a multifunctional EOG-based virtual keyboard that integrates communication and environmental control within a unified system. Eye movements with distinct polarity patterns (left, right, and down) were classified using a polarity-based approach, while similar patterns (upward gaze and blinking) were distinguished using a K-Nearest Neighbor (KNN) classifier trained on 1,000 samples and tested on 400 samples. The system integrates a virtual keyboard interface, Telegram-based messaging, and WiFi-enabled device control, and was evaluated on ten participants, including users with motor impairments. The system achieved 100% accuracy in message transmission and device control, with typing accuracy ranging from 66.7% to 100%. Reliability testing over 14 hours and 36 minutes recorded only three minor disruptions, indicating stable long-term performance. These results demonstrate that integrating multiple functions within a single EOG-based system can maintain high performance while improving usability and practical applicability. However, further validation under dynamic real-world conditions is required to ensure broader generalizability.

1. INTRODUCTION

The rapid advancement of modern technology has driven the development of various innovative solutions aimed at improving people's daily activities, particularly enhancing the quality of life of individuals with disabilities. Assistive technology plays a crucial role in addressing functional limitations and promoting higher levels of independence [1-8]. People with disabilities are defined as individuals with physical, mental, sensory, or intellectual limitations that may hinder full participation in social and functional activities [9-12]. In some cases, individuals may experience multiple disabilities, a combination of more than one type of limitation that significantly impacts adaptive capacity and level of independence [13]. Globally, the demand for assistive technology continues to increase. According to the World Health Organization (WHO), approximately 1.3 billion people, representing 16% of the global population, live with some form of disability [14]. Furthermore, more than 2.5 billion individuals require at least one assistive device, and this number is projected to reach 3.5 billion by 2050, though the need remains largely unmet [15]. This situation underscores the urgency of developing assistive systems that are not only innovative but also accessible, affordable, and adaptive. In this context, the human-computer interaction (HCI) paradigm plays a crucial role in ensuring that technological systems are designed in alignment with the capabilities, limitations, and interaction characteristics of users [16-20].

One promising direction in HCI is the utilization of biosignals as an intuitive and non-invasive communication channel between humans and machines [21-29]. Among these biosignals, electrooculography (EOG) has emerged as a powerful and widely adopted modality due to its ability to capture eye movement activity through the electrical potential difference between the cornea and retina [30, 31]. Eye movements, such as horizontal, vertical, and blinking, generate distinctive electrical patterns that can be reliably detected and offer several advantages, including low acquisition cost, high temporal resolution, and fast response [5, 10, 11, 31-35].

Recent research trends indicate a significant shift towards the integration of machine learning and deep learning techniques in EOG-based systems to improve classification performance and noise robustness. Techniques such as convolutional neural networks (CNNs), hybrid models, and adaptive algorithms demonstrate robust capabilities in handling complex, noisy, and user-dependent biosignals [36-44]. A recent systematic literature review analyzing 59 studies published between 2019 and 2025 confirms this trend, with approximately 61% of eye movement-based virtual keyboard systems adopting artificial intelligence approaches, with deep learning models being the dominant choice due to their ability to model nonlinear relationships in biosignals. However, most studies still rely on limited-scale datasets dominated by healthy participants in controlled laboratory settings, thus limiting generalizability to real-world conditions [45].

While numerous studies have demonstrated significant progress in the development of EOG-based systems, most existing approaches still focus on a single function and are developed in isolation, such as text-based communication systems, mobility control, or environmental interaction. Virtual keyboard systems have achieved high levels of accuracy and efficiency through the implementation of adaptive layouts and asynchronous interaction mechanisms [19, 20, 24-28, 46]. Meanwhile, mobility systems have demonstrated reliable control performance using machine learning-based classification approaches [1, 47], including EOG-based robotic device control applications for assistive tasks [48]. Intelligent environmental systems have also provided promising usability results in real-world scenarios [4]. However, most of these systems remain single-function solutions that operate separately without integration into a unified platform. This fragmentation poses significant limitations in real-world applications, especially for users with severe disabilities who require seamless interaction across multiple activities, such as communication, environmental control, and digital connectivity. Furthermore, many previous studies have focused more on improving classification accuracy while paying less attention to system integration, usability, and long-term operational stability. These limitations reveal a clear gap in the development of EOG-based HCI systems that are not only algorithmically accurate but also integrated, multifunctional, and ready for use in real-world contexts.

To address these gaps, this study proposes a multifunctional virtual keyboard system based on EOG signals that integrates communication and electronic device control within a unified interface. Unlike prior studies that develop isolated solutions, the proposed system enables users to perform multiple tasks simultaneously within a single platform. The main contributions are fourfold. First, the system integrates an EOG-based virtual keyboard with a real-time communication platform via the Telegram API, enabling users to compose and send messages using eye movements. Second, it combines text input, messaging, and device control within a unified system. Third, a hybrid classification approach is developed by combining polarity-based detection with the K-Nearest Neighbors (KNN) algorithm to distinguish signals with similar characteristics. Although prior studies have demonstrated the dominance of CNNs in biosignal classification, the selection of KNN in this study is driven by the alignment between data characteristics and system requirements. In particular, the limited-scale dataset inherent in experimental settings, a common characteristic in biosignal-based research, renders deep learning models suboptimal, as they typically require large volumes of data to achieve robust generalization and mitigate overfitting [49]. In contrast, KNN, as a computationally efficient non-parametric method, provides stable performance under limited data conditions without requiring complex training procedures [50]. Furthermore, the structured and distinguishable nature of EOG signals enables reliable classification using feature- and distance-based approaches without the need for deep hierarchical feature extraction [51, 52]. Therefore, KNN is adopted as a practical and efficient baseline model, aligned with both the data characteristics and real-time operational requirements. Fourth, this study extends beyond algorithmic performance by incorporating a comprehensive user-centered evaluation involving both healthy participants and individuals with disabilities, including long-term reliability and usability analysis. The system is designed for real-world deployment, emphasizing computational efficiency and real-time operation on resource-constrained devices. The results indicate that the proposed system achieves high performance across multiple evaluation dimensions, including accuracy, reliability, and usability, while maintaining stable operation over extended use. These findings underscore the importance of transitioning from isolated, algorithm-focused approaches toward integrated system design in next-generation assistive technologies.

2. RELATED WORK

Research on EOG-based HCI systems has advanced significantly, particularly in assistive applications for individuals with motor impairments. Existing studies can be broadly categorized into three domains: communication, mobility, and environmental interaction. In communication, EOG-based virtual keyboards have achieved high accuracy and efficiency through adaptive layouts, regression-based detection, and asynchronous interaction models [19, 20, 24-28, 46, 47]. However, these systems are primarily limited to text input and do not support broader interaction functionalities.

Beyond communication, EOG-based systems have also been applied in mobility and environmental interaction contexts. Machine learning approaches, such as Support Vector Machines (SVM) and decision tree methods, have been used for wheelchair navigation [1, 48], while other studies demonstrate real-time control in robotic manipulation and virtual environments [8, 18, 49]. In addition, EOG-based smart home systems enable device control within Internet of Things (IoT) environments [4]. Despite their effectiveness, these systems remain task-specific and lack integration across multiple interaction domains. Recent advancements in artificial intelligence have further improved EOG-based systems, with machine learning and deep learning models (e.g., CNNs, RNNs, and hybrid approaches) enhancing classification accuracy and robustness [36-44]. However, their effectiveness is often constrained by the availability of large-scale datasets, which remains a common limitation in EOG-based research.

A systematic literature review covering 59 studies published between 2019 and 2025 indicates that most EOG-based systems are developed using small-scale datasets, which reflects a common constraint in biosignal-based research due to the complexity of data acquisition and limitations in participant recruitment [45]. While these systems often achieve high accuracy, typically above 90%, their reliance on controlled laboratory conditions and datasets dominated by healthy participants limits generalizability to real-world scenarios. This characteristic is also present in the current study, where data collection involves a limited number of participants, reflecting typical experimental conditions in EOG-based system development. Under such constraints, lightweight and data-efficient models, such as KNN, become more suitable compared to data-intensive deep learning approaches, as they can provide stable performance without requiring large training datasets. Overall, the literature reveals a consistent gap: existing EOG-based systems are predominantly single-function, rely on limited datasets, and lack comprehensive evaluation in real-world scenarios. This fragmentation restricts their practical applicability, particularly for users requiring seamless interaction across multiple tasks.

To address these limitations, this study proposes a multifunctional EOG-based system that integrates communication and environmental control within a unified interface. The system combines a hybrid classification approach using polarity-based detection and KNN with a comprehensive user-centered evaluation. A structured comparison of representative studies is presented in Table 1, highlighting the limitations of existing systems and the advantages of the proposed approach.

Table 1. Comparative analysis of representative electrooculography (EOG)-based Human-Computer Interaction (HCI) systems in terms of methodology, application, and system capabilities

Study	Modality	Method	Application	Accuracy	Dataset	Real-Time	Multi-Function	Limitation
[1, 48]	EOG	SVM	Wheelchair Control	~ 95-98%	Small-scale	Yes	No	Direction-only control
[2]	EOG	ML + Simulation	Navigation	High (reported)	Laboratory-controlled	Yes	No	Limited real-world validation
[4, 8]	EOG	Threshold / ML	Smart Home / Robotics	> 90%	Limited dataset	Yes	No	Single-domain functionality
[19,20]	EOG	Threshold / ML	Virtual Keyboard	~ 90-99%	Small-scale (healthy-dominant)	Yes	No	Single-task interaction
[24-28]	EOG	Regression	Text Input	> 90%	Laboratory-controlled	Yes	No	Sensitive to noise
[28, 46, 47]	EOG	Hybrid + Prediction	Virtual Keyboard	> 90%	Limited dataset	Yes	No	Limited generalization
SLR [45]	Multi-modal	AI (CNN dominant)	Various	> 90%	Mostly small-scale (healthy users)	Mostly No	Rare	Poor generalization, limited real-world validation
Proposed	EOG	Hybrid (Polarity + KNN)	Communication + Control	66.7-100%	Real users (healthy + disabled, n = 10)	Yes	Yes (Integrated)	Small sample size

Note: Support Vector Machines (SVM); convolutional neural network (CNN); K-Nearest Neighbor (KNN); Machine Learning (ML)

3. METHODOLOGY

This research uses an applied experimental approach with the aim of developing a multifunctional virtual keyboard system based on EOG signals. This system is designed to be able to carry out two main functions simultaneously, namely sending digital messages through integration with the Telegram API and controlling microcontroller-based electronic devices.

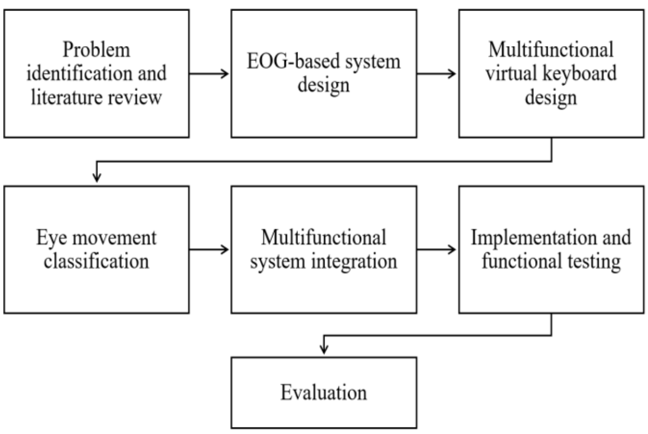


Figure 1. Block diagram of research stages

The system was developed as a laboratory prototype intended for individuals with motor and multiple disabilities who also experience speech disorders, so they cannot use fingers or voice commands as input media. The stages of this research include: (1) problem identification and literature study (2) design of an EOG-based virtual keyboard system (3) acquisition and preprocessing of EOG signals (4) classification of eye movements (5) integration of the multifunctional system (6) implementation and functional testing (7) performance evaluation and analysis of results (8) conclusions and recommendations. These stages can be seen in Figure 1.

3.1 Problem identification and literature review

The initial stage of the research began with identifying the needs of users with motor and speech disabilities through literature studies and observations of existing assistive systems. The results showed that most previous EOG-based keyboard systems were still limited to one-way typing functions and had not been integrated with device control systems or digital communication platforms. Based on this gap, this research focused on designing a multifunctional biosignal-based system that could perform two functions in a single interface and was easy to use.

3.2 Electrooculography-based system design

Figure 2 shows a diagram of the overall system design, which combines two main, integrated components: hardware and software.

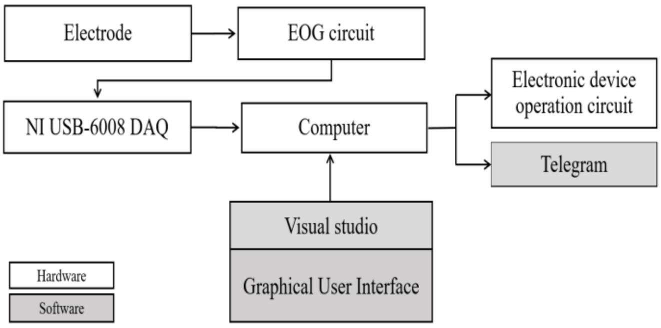


Figure 2. Overall block diagram of an electrooculography (EOG)-based virtual keyboard system

Table 2. Morphological chart of the main menu display

Sub-Function	Options
Background and button color	Combination 1: 3 white buttons on black background Combination 2: 3 black buttons on white background Combination 3: 3 blue buttons on white background Combination 4: 3 blue buttons on black background
Bold font	Yes No
Button size	95 × 30 px 95 × 50 px 95 × 95 px
Text design	Lowercase Uppercase Capitalized
Button position	Top-bottom Left-right
Includes image	Yes No

The hardware part is designed to capture, amplify, and convert EOG signals into digital data ready for processing. Meanwhile, the software part is responsible for processing the data, displaying a virtual keyboard interface, and sending commands to electronic devices and messages via the Telegram application. The integration of these two components allows the system to work as a whole, detecting eye activity, translating it into commands, and realizing communication and control functions for electronic devices for users. To explain each component shown in the diagram in more detail, the following outlines the system's design stages in a structured manner. The first stage is the electrode, which detects electrical signals from eye activity and transmits them to the EOG circuit. The initial signal is then amplified and filtered to allow only relevant EOG signals to be transmitted to the NI USB-6008 data acquisition device. The signal is then converted into digital data, which is processed by a computer or laptop, which also serves as a user interface for operating a multifunction virtual keyboard. Command output from this keyboard is used to control electronic equipment, while the graphical interface is developed using Visual Studio. To support communication functions, the system utilizes the Telegram application, integrated through an API.

3.3 Multifunctional virtual keyboard design

The virtual keyboard in this study functions to send messages and operate electronic devices. The virtual keyboard's display is constructed using a morphological chart consisting of a main menu display, a general word display, a message sending display, a keyboard display, and a display for operating the electronic device. The following is a morphological chart for each virtual keyboard display.

Participants evaluated several layout options based on:

a. Visibility: ease of seeing and recognizing the keys.

b. Visual comfort: comfort of the colors used for the eyes.

c. Ergonomics: comfort in reaching the desired keys.

The result of most participants' choices was determined as the final design for the virtual keyboard. Each interface component was designed based on the most preferred configuration, as summarized in Tables 2-6.

Table 3. Morphological chart of the common words display

Sub-Function	Options
Text design	Lowercase Uppercase Capitalized
Back, send to, keyboard buttons	Model 1: back (left), keyboard (right), send to (bottom) Model 2: back (left), keyboard (right), send to (right) Model 3: back (left), keyboard (right), send to (left) Model 4: back (bottom), keyboard (right), send to (bottom) Model 5: back (left), keyboard (bottom), send to (bottom) Model 6: back (bottom), keyboard (bottom), send to (bottom) Model 7: back (right), keyboard (right), send to (right)
Word text position	Top Bottom Left Right
Includes image	Yes No

Table 4. Morphological chart of the messaging display

Sub-Function	Options
Button properties	Static Adaptive
Button size	75 × 20 px 75 × 35 px 75 × 75 px
Text design	Lowercase Uppercase Capitalized
Message text position	Left Right Top Bottom
Position of send and back buttons	Left-Right Bottom Top
Includes image	Yes No

Table 5. Morphological chart of the keyboard display

Sub-Function	Options
Keyboard type	Qwerty
	Alphabet
Text design	Lowercase
	Uppercase
Back and send button position	Left-right
	Bottom
	Top
Message text position	Top
	Bottom
	Left
	Right

Table 6. Morphological chart of the electronic equipment control display

Sub-Function	Options
Button style	On/off combined
	On/off separated
Equipment description	Text
	Image
Text design	Lowercase
	Uppercase
	Capitalized
Position of back button	Left
	Right
	Bottom
	Top

3.4 Eye movement classification

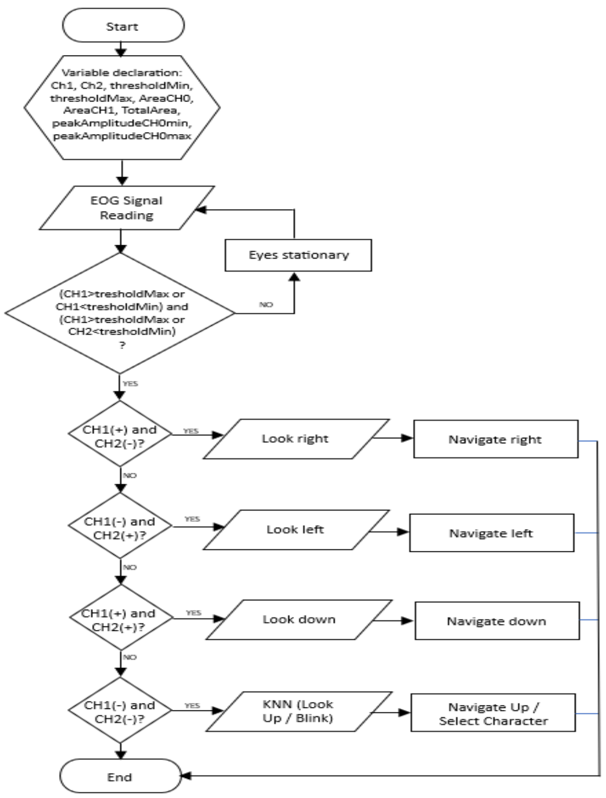


Figure 3. Signal classification flowchart

A software-based classification framework was developed to interpret EOG signals using polarity features and the KNN algorithm. The system translates eye movements, left, right, up, down, and blink, into navigation commands for the virtual keyboard. Polarity-based classification is applied to directly distinguish left, right, and downward movements due to their distinct signal polarities. However, upward gaze and blinking exhibit similar polarity patterns; therefore, a K-NN classifier is employed to differentiate these signals. The overall classification process is illustrated in Figure 3.

3.4.1 Signal acquisition and preprocessing

The dataset used in this study consists of 1,400 labeled EOG signal samples collected from 10 participants, including 8 healthy individuals and 2 users with mild motor disabilities, representing a heterogeneous user group. Each participant contributed multiple samples across different eye movement classes. EOG signals were acquired using a two-channel configuration, with electrodes positioned below the right eye (Ch1) and on the left outer canthus (Ch2), while a reference electrode was placed on the nasal bridge and the ground electrode on the forehead.

The analog signals were amplified using an instrumentation amplifier (gain = 1000) and filtered using a 0.1-30 Hz band-pass Butterworth filter (4th order) to remove baseline drift and electromyographic noise. The signals were sampled at 1 kHz using an NI USB-6008 interface and normalized using Min-Max scaling. This preprocessing pipeline ensures consistent signal representation across participants and reduces inter-subject variability.

All data were collected under controlled laboratory conditions to ensure signal stability. External noise factors, such as varying lighting conditions and unrestricted head movement, were not explicitly incorporated. While this setup enables controlled evaluation of the proposed method, it may limit generalizability to dynamic real-world environments.

3.4.2 Thresholding and polarity determination

A dynamic thresholding procedure was applied based on participant-specific baseline signals. The baseline amplitude was recorded during a 5-second resting period, and the threshold was computed as:

$$T = \mu_{rest} + \sigma_{rest}$$

where, μ_{rest} and σ_{rest} represent the mean and standard deviation of the resting signal, respectively. The threshold values typically ranged from + 0.45 to + 0.55 V. Eye movements exceeding ± T were classified as significant events.

Polarity analysis was then used to directly classify left, right, and downward movements based on the sign differences between channels Ch1 and Ch2. This approach enables fast and computationally efficient classification for signals with distinct polarity characteristics, reducing the need for more complex models.

3.4.3 K-Nearest Neighbor classification for upward gaze and blinks

Since upward gaze and blinking exhibit similar polarity patterns, a KNN classifier is employed to distinguish these two classes. Three features are extracted from the EOG signals: maximum amplitude, area under the curve (AUC), and polarity direction. Euclidean distance is used as the similarity metric. The optimal K value is determined through experimental evaluation using K = 1-5 on a validation set. While K = 1, 2, and 4 achieve perfect accuracy, these configurations are more prone to overfitting, particularly for K

= 1. In contrast, K = 3 achieves 99.75% accuracy with improved generalization, as supported by confusion matrix analysis. Therefore, K = 3 is selected as the optimal parameter to balance accuracy and robustness.

The dataset is randomly shuffled and divided using a hold-out strategy into 1,000 training samples (500 upward gaze and 500 blinks) and 400 testing samples (200 upward gaze and 200 blinks), corresponding to an approximate 71:29 split. Both sets are derived from the same participants but are separated to ensure evaluation. This classification approach operates on preprocessed signals to ensure consistent feature representation across users. Although filtering and thresholding help mitigate noise interference, the system is evaluated under controlled conditions; therefore, robustness to dynamic noise remains a limitation and an important direction for future work.

3.5 Multifunctional system integration

This system integrates communication and electronic device control within a single virtual keyboard interface. The communication function is implemented using the Telegram API, while environmental control is achieved using an ESP32-based WiFi relay module for operating household devices such as lights and fans. The ESP32 is selected due to its real-time processing capability, low power consumption, and integrated WiFi connectivity, making it suitable for embedded IoT-based assistive systems. Compared to Arduino and Raspberry Pi, it offers a more balanced trade-off between computational efficiency, connectivity, and system complexity.

Communication between modules is performed via asynchronous serial and WiFi protocols, achieving an average latency of 30-60 ms, which is sufficient for real-time interaction. The system operates reliably for single-device and small-scale multi-device control under controlled conditions, although scalability and long-term stability in larger deployments remain areas for future work. This integrated design enables seamless operation as both a communication tool and an electronic device controller. Figure 4 illustrates the system operation sequence.

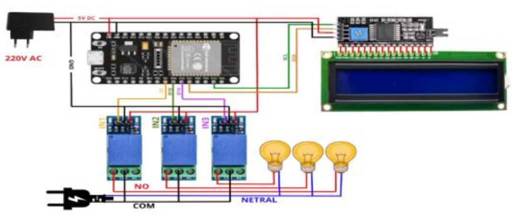


Figure 4. Electronic equipment operating circuit

3.6 Implementation and functional testing

The proposed system was implemented and evaluated in a controlled laboratory environment involving ten participants (eight healthy individuals and two users with mild motor disabilities). These participants are the same individuals involved in the dataset acquisition process described in Section 3.4. During testing, participants were instructed to execute predefined tasks using eye-gaze interaction.

Functional testing was conducted to verify the integration and synchronization of system components, from EOG signal acquisition to interface responsiveness. The evaluation focused on three core functionalities: text input, message transmission via Telegram, and control of electronic devices through the virtual keyboard interface.

System performance was assessed using three task-based criteria: accuracy, reliability, and ease of use. Accuracy was measured as the proportion of correctly executed commands during task completion, with any incorrect command classified as an error. Reliability was evaluated by observing the consistency of system responses across repeated task executions at different time intervals, including the occurrence of delays, glitches, or unexpected behavior. Ease of use was assessed by measuring the time required for participants to learn the system and by observing any difficulties or need for assistance during operation.

All tasks were performed repeatedly, and system responses were systematically recorded, including successful executions, errors, response delays, and abnormal behavior. These observations formed the basis for subsequent performance evaluation.

3.7 Evaluation

The evaluation was conducted using a task-based observational approach to assess the performance of the proposed EOG-based multifunctional virtual keyboard system. Participants were required to perform a series of predefined tasks, including character selection, text input, message transmission via Telegram, and control of electronic devices using eye-gaze interaction.

During task execution, system performance was evaluated based on three variables: accuracy, reliability, and ease of use. Accuracy was defined as the system's ability to correctly interpret eye movements and execute the intended commands. Reliability referred to the consistency of system performance across repeated trials under similar conditions. Ease of use was defined as the level of effort required to learn and operate the system, evaluated through learning time, user dependency, and observed interaction difficulties.

Throughout the evaluation, system responses, interaction stability, and operational consistency were continuously monitored. Any errors, delays, or unexpected behaviors were recorded and analyzed to assess overall system performance. The evaluation results were used to determine the system's effectiveness in supporting communication and electronic device control through eye-gaze interaction, particularly for users with disabilities. Additionally, it should be noted that the limited number of participants and the dominance of healthy subjects may introduce potential bias, which could affect the generalizability of the results to broader real-world scenarios.

4. RESULT

This multifunctional virtual keyboard is designed to enable individuals with disabilities to communicate and operate electronic devices through EOG signals. The working stages of this system are as shown in the Figure 5.

4.1 Experimental setup and participants

The system was evaluated using ten participants with diverse age ranges and physical conditions, consisting of six males and four females. The participant ages included 72, 55, 30, and 24 years for females, and 58, 32, 27, 23, 22, and 20 years for males. Among them, two participants had motor impairments, namely a 72-year-old female with paralysis and speech difficulty and a 58-year-old male with limited mobility, while the remaining participants were healthy individuals. This heterogeneous composition enables the evaluation of system performance across different age groups and user conditions, while the inclusion of elderly and motor-impaired participants provides additional insight into system usability and robustness in diverse real-world scenarios.

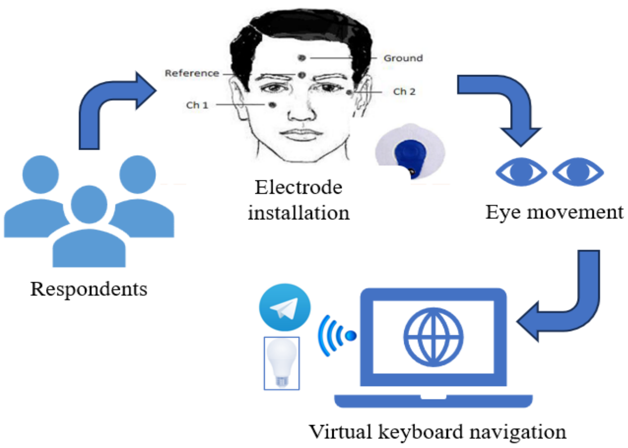


Figure 5. Electrooculography system working stages

The EOG system circuit is shown in Figure 6 and is powered by a 9V DC source. It consists of electrode inputs (Ch1, Ch2, Reference, Ground), voltage supply connections, and analog outputs. The electrode placement on participants is illustrated as part of the system workflow in Figure 5. A two-channel configuration is used to capture vertical and horizontal eye movements. The Ch1 electrode, positioned below the right eye, detects vertical activity, where upward movements produce positive amplitudes and downward movements produce negative amplitudes. The Ch2 electrode, placed on the outer canthus of the left eye, captures horizontal activity, with rightward movements generating positive signals and leftward movements producing negative signals. The Reference electrode, located on the nasal bridge, provides a stable baseline, while the Ground electrode on the forehead reduces electrical interference and electromyographic noise.

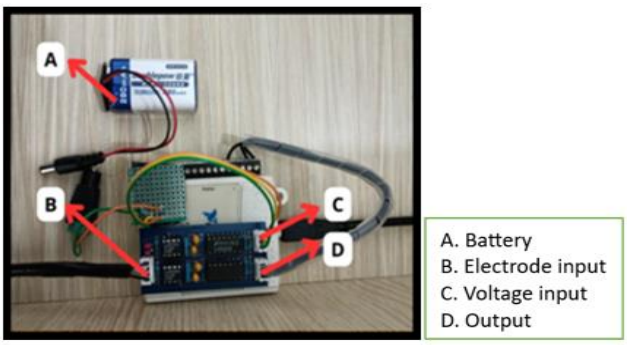


Figure 6. Implementation of the electrooculography (EOG) circuit

A comparison of the actual and simulated EOG circuits is shown in Figure 7, showing fairly consistent EOG signal voltage patterns. While there are some minor differences in signal amplitude and fluctuation, overall the simulation provides a good prediction of actual performance. These minor differences may be due to external factors in real-world measurements that are difficult to simulate precisely.

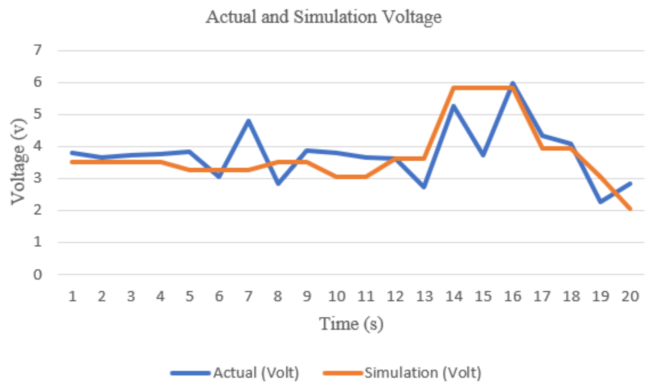


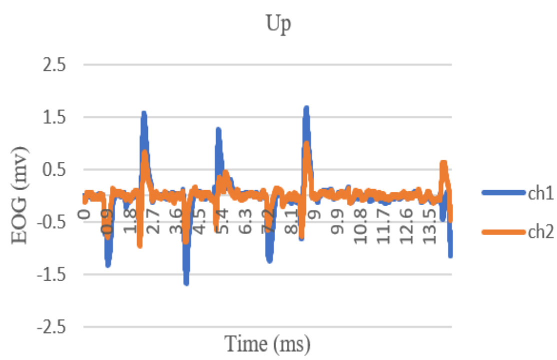
Figure 7. Comparison of voltage output (v) between the actual and simulated electrooculography circuits for hardware validation

4.2 Signal classification

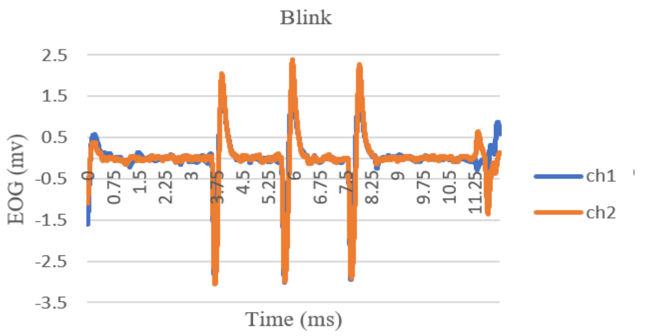
Based on data obtained from participants, the threshold values were set at 0.5 V for positive polarity and -0.5 V for negative polarity at the output level of the EOG circuit when the participants were in a stationary condition. The difference in scale between volts and millivolts is due to signal amplification in the acquisition circuit. The voltage in volts represents the amplified circuit output, while the EOG signals are expressed in millivolts (mV) to reflect physiological signal amplitude during analysis and classification, as illustrated in Figure 8. Signals with amplitudes exceeding the threshold values were then classified based on their polarity differences. Signals with similar polarity were further analyzed using the KNN method to ensure the accuracy of eye movement classification. The classification process follows the training and testing configuration described in Section 3.4.3.

The features used to classify upward gaze and blinking signals include signal polarity, signal area, and maximum signal amplitude. The performance of the KNN algorithm with varying K values is presented in Table 7. The highest accuracy (100%) is achieved for K = 1, 2, and 4. However, these configurations are more prone to overfitting, particularly for K = 1, where the model becomes highly sensitive to the training data and less capable of generalizing to new samples. To balance accuracy and generalization, K = 3 is selected as the optimal value, achieving 99.75% accuracy with improved generalization performance compared to smaller K values.

It should be noted that the evaluation was conducted using data derived from the same participants as described in the Section.



(a)



(b)

Figure 8. Processed electrooculography (EOG) signals (mV) with the same polarity: (a) upward gaze, (b) blink

While this setup enables controlled evaluation, it may introduce subject-dependent bias and limit generalizability to unseen users.

Table 7. Variation of neighboring K values

Number of K	Number of Test Data	Accuracy (%)
1	400	100.00
2	400	100.00
3	400	99.75
4	400	100.00
5	400	99.50

4.3 Virtual keyboard interface and control system

Participants selected the virtual keyboard layout based on visibility, visual comfort, and ergonomics using a morphology chart. This layout consists of five sections: main menu, common words, messaging, keyboard, and electronic device operation. Ten Participants selected the options on the morphology chart for this virtual keyboard layout. Table 8 presents the results of this selection, demonstrating a clear preference for interface elements that emphasize clarity and operational consistency. The majority of participants selected all-caps text, standard key sizes, left-right placement for send/return commands, and the use of supporting icons throughout the module. These dominant preferences formed the basis for the final interface configuration. The implemented interface, illustrated in Figure 9, reflects the cumulative results of these design decisions. Each panel, from the main menu to the device control display, integrates the color scheme, iconography, and spatial arrangement selected by the participants. As a result, the final multifunctional virtual keyboard layout exhibits visual uniformity and enhanced usability, making it well-suited for EOG-based control.

The electronic device control system enables users to operate household appliances through a virtual keyboard interface. Devices such as fans, lamps, televisions, refrigerators, washing machines, and speakers are represented using icons with ON/OFF controls, arranged in a grid layout to support efficient navigation via EOG-based commands. The hardware module (Figure 10) is based on an ESP32 microcontroller functioning as the central controller, connected to relay switches for controlling 220 V AC devices. Commands are transmitted wirelessly via WiFi from the virtual keyboard to the control module. The circuit includes load indicators, a 220 V AC power input, an LCD display for real-time status and IP address monitoring, a reset button, and a main power switch. Real-time feedback from the LCD ensures synchronized operation between the software interface and hardware module. This integration allows eye movement commands to be reliably translated into physical device control.

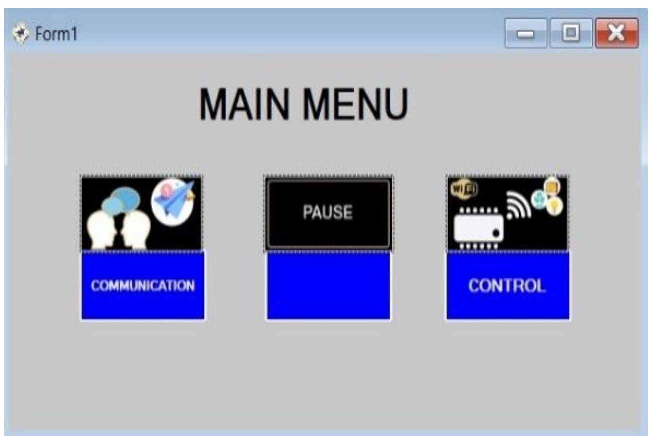
Table 8. Summary of interface design decisions

Component	Design Result	n = 10
Main menu	Color Combination 3	6
	Bold and uppercase text	10
	Button size 95 × 50	6
	Horizontal layout	8
	Icons applied	9
Common words	Uppercase text	8
	Model 1 layout (Send right-Back left)	4
	Text positioned at top	10
	Icons applied	9
Message sending	Static buttons	10
	Button size 75 × 35	7
	Uppercase text	8
	Text positioned at top	10
	Left-right button layout	7
	Icons applied	9
Main keyboard	Alphabetic keyboard	7
	Uppercase text	10
	Left-right layout	5
	Text positioned at top	10
Device control	Combined On/Off toggle	9
	Icon-based labels	8
	Uppercase text	8
	Back button on the left	7

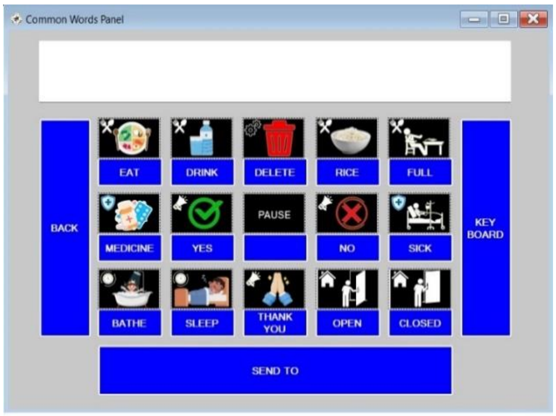
4.4 Accuracy evaluation

Accuracy testing involved typing the five-letter word "MINUM," sending it, and operating a connected device. Each participant performed three trials. The system achieved 100% accuracy for both message transmission and device control, while typing accuracy ranged from 66.7% to 100%.

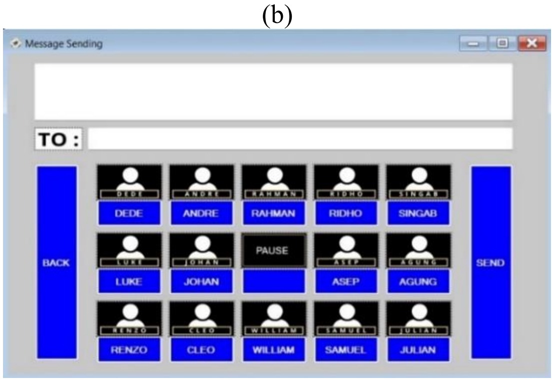
Based on participant characteristics, younger participants (20-32 years, n = 7) achieved typing accuracy ranging from 86.7% to 100%, whereas older participants (55-72 years, n = 3) demonstrated lower performance, ranging from 66.7% to 86.7%, as summarized in Table 9. The lowest accuracy (66.7%) was observed in the 72-year-old participant, while the other older participants also exhibited lower performance compared to younger users. This variation may be associated with differences in familiarity with digital interfaces, response speed, and motor capabilities among user groups.



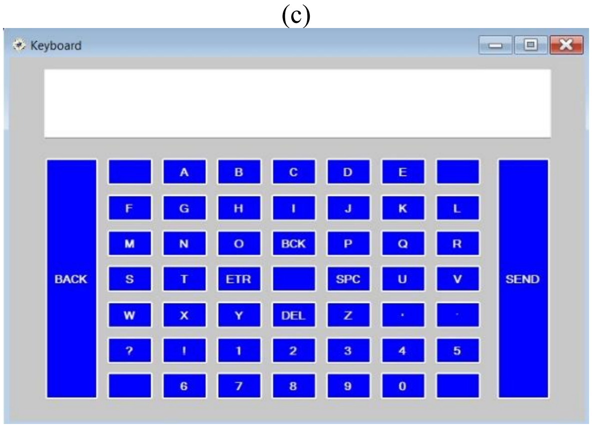
(a)



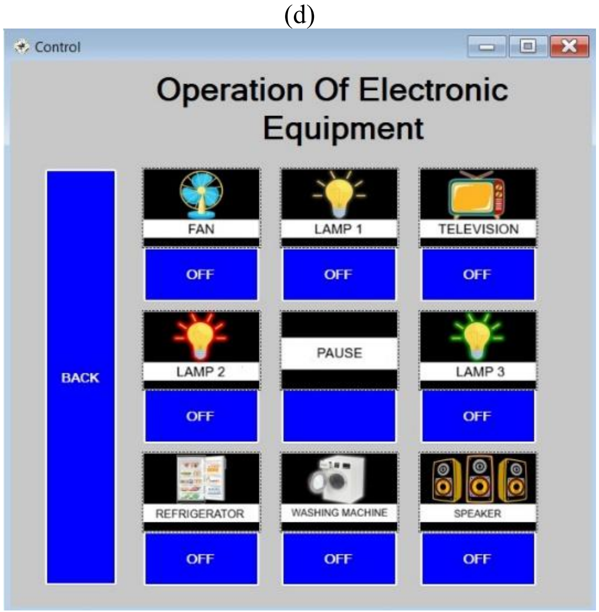
(b)



(c)



(d)



(e)

Figure 9. Graphical interface of the multifunctional virtual keyboard system: (a) main menu, (b) common words panel, (c) message sending, (d) main keyboard, (e) device control

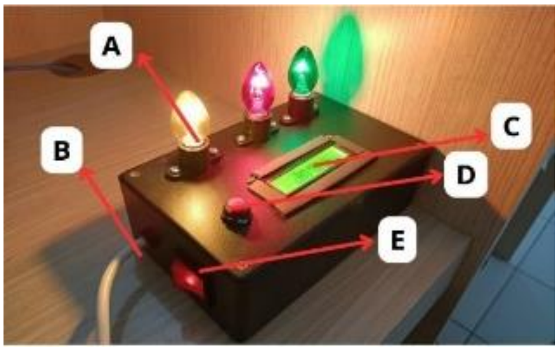


Figure 10. Implementation of electronic equipment operating circuit

Table 9. Comparative accuracy based on age group

Age Group	Participants Count	Accuracy Range
20-32 years	7	86.7-100%
55-72 years	3	66.7-86.7%

Figure 11 presents the accuracy testing results of the multifunctional virtual keyboard. The system achieved 100% accuracy in message transmission and device control, indicating reliable system performance. In contrast, typing accuracy ranged from 66.7% to 100%, with the lowest performance observed in the 72-year-old participant. Overall, younger participants demonstrated higher accuracy compared to older participants, consistent with the distribution presented in Table 9.

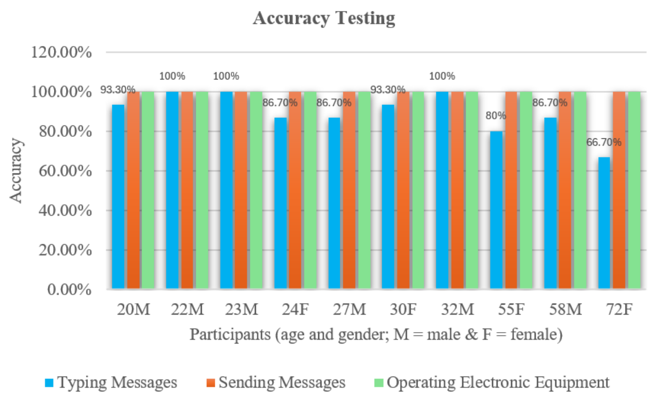


Figure 11. Accuracy testing graph of multifunctional virtual keyboard

The participants' age range varied from younger participants (20-32 years) to older ones (55-72 years). Younger participants tend to have a higher success rate (86.7% and above), while older participants show lower rates, such as a 72-year-old female with 66.7%. This difference may be attributed to variations in familiarity with digital interfaces and response speed across age groups.

4.5 Reliability assessment

The reliability testing of the multifunctional virtual keyboard was conducted by recording the number of disturbances and the types of disturbances that occurred during use by the participants.

Figure 12 shows that the success rate outweighed the error rate. The most common problem encountered during the virtual keyboard use was when the keyboard stopped responding to commands. A total of 20 trials were conducted, with the total operational time of the virtual keyboard reaching 14 hours and 36 minutes. Out of all these trials, only three disruptions were recorded. This indicates that the virtual keyboard has a fairly high reliability level, with a success rate of 85% (17 out of 20 trials) being completed without any disruptions.

Figure 12. Reliability testing chart of the multifunctional virtual keyboard

4.6 Usability and learning adaptation

The usability testing of the multifunctional virtual keyboard was conducted by asking new participants to learn how to operate it. Based on Figure 13, it can be seen that most participants did not require assistance, indicating that the tested virtual keyboard is relatively easy to use. However, older participants took longer to learn compared to younger participants. This is due to the tendency of younger participants to adapt more quickly to new technologies.

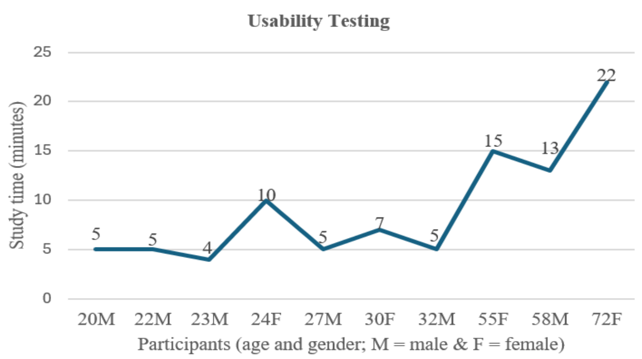


Figure 13. Graph of multifunctional virtual keyboard usability testing

5. DISCUSSION

This study addresses a key gap identified in the literature, namely the fragmentation of EOG-based systems across isolated functional domains such as communication, mobility and interaction, and environmental control systems. While prior studies demonstrate high classification accuracy and strong task-specific performance, their limited integration restricts real-world applicability. Accordingly, this study shifts the focus from algorithm-centric performance toward an integrated HCI system capable of supporting multiple user needs within a unified platform.

In communication systems, EOG-based virtual keyboards have reached high algorithmic maturity, including near-perfect detection accuracy and improved efficiency through asynchronous input and adaptive layouts [20, 25, 28]. However, as shown in Table 10, these systems remain limited to text input and lack environmental control capabilities. Similarly, mobility and interaction systems achieve high control accuracy and low error rates [18, 47], while environmental control systems demonstrate strong usability and real-time responsiveness [4]. Despite these strengths, all remain task-specific and lack cross-functional integration, reinforcing structural separation in existing EOG-based solutions. In parallel, algorithm-centric studies improve classification performance using machine learning and deep learning methods [21, 36-44], yet are largely confined to signal classification without extending to complete HCI system implementation. This confirms that algorithmic performance alone is insufficient without functional integration.

Several studies also emphasize usability without adequate quantitative validation. Although gaze- and blink-based interfaces are often described as intuitive, the absence of consistent performance metrics limits reproducibility and objective evaluation [24, 45]. This underscores the need for balanced evaluation combining usability with measurable performance indicators. The findings of this study indicate that the primary challenge in modern EOG systems is no longer classification accuracy, but system-level integration across multiple interaction functions. The proposed system addresses this gap by integrating communication and environmental control within a single platform while maintaining competitive performance in accuracy, reliability, and usability. These results demonstrate that high performance can be achieved alongside functional integration, highlighting system-level design, usability, and adaptability as key requirements for real-world assistive technologies. To further illustrate this limitation, Table 10 presents a comparative analysis of existing EOG-based systems based on functional integration. As shown in Table 10, most existing systems remain task-specific, lacking integration across multiple interaction domains, thereby reinforcing the fragmentation identified in the literature.

Although the proposed system demonstrates strong performance under controlled laboratory conditions, several challenges may arise in real-world deployment. Variations in lighting conditions and electrical interference may affect signal quality and classification stability. While filtering and thresholding help mitigate noise interference, their effectiveness under highly dynamic conditions requires further investigation. In addition, the evaluation was conducted on a relatively small sample of 10 participants, which may not fully represent the diversity of end users, particularly individuals with varying levels of motor impairment, potentially affecting generalizability. Future work will therefore focus on improving robustness through adaptive signal calibration and advanced noise-handling techniques, as well as conducting large-scale evaluations involving more diverse user populations.

Table 10. Comparative analysis of existing electrooculography-based systems and the proposed approach based on functional integration

System Category	Studies	Primary Function	Typical Methods	Reported Performance	Key Limitations
Communication Systems	[19, 20, 24-28, 46, 47]	Text input / virtual keyboard	Threshold-based, regression, ML	High accuracy (~ 90-99%); improved typing efficiency	Limited to text input; no environmental or multi-task integration
Mobility and Interaction Systems	[1, 18, 49]	Wheelchair navigation, robotic control	SVM, threshold-based, vision-assisted	~ 96-98.89% control accuracy; low interaction error	Task-specific; lacks communication functionality
Environmental Control Systems	[4, 8]	Smart home / device control	Threshold-based, IoT-based control	High usability (SUS > 89); real-time responsiveness	No text communication; limited interaction flexibility
Algorithm-Centric Studies	[21, 36-44]	Signal classification	CNN, RNN, hybrid deep learning	High classification accuracy (> 90%)	Focus on algorithms only; lacks system-level implementation
Proposed System	This study	Integrated communication and device control	Hybrid (polarity + KNN)	100% control accuracy; 66.7-100% typing; stable real-time performance	Limited dataset; controlled environment

Note: Support Vector Machines (SVM); convolutional neural network (CNN); K-Nearest Neighbor (KNN); Machine Learning (ML)

6. CONCLUSION

This study demonstrates that the primary limitation in EOG-based assistive interfaces lies not in signal classification accuracy, but in the fragmentation of system functionality. Previous studies have achieved high performance on isolated tasks such as text input, mobility control, and environmental interaction; however, these capabilities are rarely integrated within a coherent HCI framework. By developing an integrated EOG system that combines communication and environmental control, this study shows that high algorithmic performance can be maintained while expanding functional capability. The results confirm stable real-time operation and effective task execution without compromising usability. These findings highlight that system-level integration is a more critical factor than classification accuracy alone for real-world assistive applications. Future work will focus on improving robustness under dynamic environmental conditions, conducting large-scale user validation, and enhancing integration with external platforms and smart environments to support broader real-world deployment.

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