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AI-Driven Eye-Controlled Virtual Keyboard Systems for Motor-Impaired Users: A Systematic Literature Review of Biosignal and Vision-Based Interaction Modalities

Putri Mandarani[1,2], Muhammad Ilhamdi Rusydi[1*], Rahmadi Kurnia[1], Budi Sunaryo[1,3]

[1] Department of Electrical Engineering, Faculty of Engineering, Universitas Andalas, Padang 25163, Indonesia
[2] Department of Informatics Engineering, Faculty of Engineering, Institut Teknologi Padang, Padang 25143, Indonesia
[3] Department of Network Computer Engineering Technology, Faculty of Industrial Technology, Universitas Bung Hatta, Padang 25133, Indonesia

Corresponding Author Email: rusydi@eng.unand.ac.id

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ABSTRACT

This study presents a systematic literature review (SLR) of artificial intelligence–enabled eye-controlled virtual keyboard systems designed to support hands-free interaction for individuals with motor impairments. Following the PRISMA protocol, 59 peer-reviewed studies published between 2019 and 2025 were systematically collected and analyzed from major scientific databases, including IEEE, ScienceDirect, Springer, and MDPI. The review examines key dimensions of these systems, including input acquisition modalities, dataset characteristics, artificial intelligence architectures, evaluation metrics, and practical deployment constraints. The results indicate that approximately 61% of the reviewed systems incorporate artificial intelligence, with Convolutional Neural Networks (CNNs) emerging as the dominant approach due to their effectiveness in modeling complex eye-movement patterns and handling signal variability. Among input modalities, electrooculography is the most widely adopted technique because of its high signal fidelity and robustness to environmental variations. In contrast, gaze-tracking and computer vision–based methods offer non-contact interaction but remain sensitive to illumination conditions and head movement. Multimodal interaction frameworks have therefore been increasingly explored to improve robustness and user adaptability. Despite reported accuracy levels frequently exceeding 90%, most existing studies rely on small-scale experimental datasets involving healthy participants under controlled laboratory conditions. This limitation restricts the clinical applicability and real-world generalizability of current systems. Key challenges include signal artifacts, inter-subject variability, user fatigue, and the limited inclusion of individuals with severe motor disabilities in experimental validation. Future research should focus on adaptive and explainable artificial intelligence models, multimodal sensing strategies, and large-scale user-centered evaluations to facilitate the transition from laboratory prototypes to clinically viable assistive technologies.

1. INTRODUCTION

Technological advances have improved the quality of life, but not all individuals can benefit equally. Disability, the prevalence of which is increasing due to health, environmental, and personal factors, affects approximately 1.3 billion people-or 16% of the world's population, according to the WHO (2023) [1]. People with disabilities often experience poorer health, a higher risk of mortality, and limitations in daily activities [1-5]. Motor disabilities, particularly those that limit hand and finger movements resulting from accidents, neurodegenerative disorders (e.g., ALS), cerebral palsy, stroke, or spinal cord injury [6-9], pose significant barriers to accessing digital devices that require precision input [10-13]. Assistive technology (AT) plays a crucial role in supporting the independence of people with disabilities by providing devices that improve quality of life [14-16]. The WHO in 2024 reported that more than 2.5 billion people currently need at least one assistive device, with this figure projected to increase to 3.5 billion by 2050; however, this need remains largely unmet [17]. This gap has driven human-computer interaction (HCI) research toward touchless interaction, in which physical keyboards prove less effective for individuals with motor disabilities, thereby positioning eye-controlled virtual keyboards as a critical alternative [18-23]. These systems enable hands-free communication, information access, and device control through eye movement and biological signal-based interfaces. Specifically, EOG and EEG-based approaches facilitate device control via eye movements and brain activity, demonstrating effectiveness in applications such as virtual typing, wheelchair navigation, smart home control, robotics [2, 5, 7, 10, 20, 23-36].

In the development of eye-controlled virtual keyboards, artificial intelligence (AI) plays a key role in enabling fast, accurate, and completely touchless interactions [22-24, 36, 37]. Typically, such a system involves several main stages:

acquisition of eye movement data or natural electrical signals, noise removal, pattern detection, feature extraction, and classification. Within an AI-based virtual keyboard system, eye movement information can be obtained through various modalities, including vision-based input, such as high-resolution cameras and eye trackers [38-45], as well as biosignal-based inputs, such as electrooculography (EOG) [46-56] and electroencephalography (EEG) [57-63].

Vision-based approaches remain widely adopted due to their technological maturity and relative ease of implementation. However, biosignal-based methods offer unique advantages, particularly for users with severe motor impairments. These advantages include robustness to varying lighting conditions, reduced reliance on posture and head stability, and direct physiological representation of eye movements. In contrast, conventional non-AI approaches, such as thresholding, rule-based decision-making, or template matching, have limitations in recognizing complex eye movement patterns. process [38, 60, 62]. Therefore, many studies have shifted to AI-based approaches that utilize machine learning (ML) and deep learning (DL) algorithms, including SVM, KNN, CNN, and LSTM, to enhance the accuracy, speed, and robustness of classification in eye-controlled virtual keyboard systems [4-10, 28-32, 45-51].

Although several previous literature reviews have discussed AI-based HCI, including emotion and facial expression recognition using various sensors [64] and eye gaze-based applications [65], these studies have generally focused on a single input modality in isolation. To date, a systematic review that specifically and comparatively synthesizes the implementation of artificial intelligence models across the two major technological pathways, biosignal-based approaches (EOG or EEG) and computer vision-based approaches (camera or eye tracker), particularly for virtual keyboard systems, remains absent. A thorough understanding of the differences in characteristics between electrical signals and visual data is crucial for determining the most effective artificial intelligence architectures to address technical constraints and user physiological variations.

To address this gap, the present study provides a systematic literature review (SLR) that comprehensively maps and compares the integration of artificial intelligence across diverse eye movement input modalities, both biosignal-based and vision-based. By incorporating these two approaches, this article offers an in-depth analysis of the trade-offs between technical accuracy, signal stability, and user comfort across different input modalities. Finally, the review evaluates dataset characteristics, participant profiles, and performance metrics to formulate a future research agenda that is more inclusive of people with motor disabilities.

2. METHODOLOGY

This article employs a SLR, a scientific research method used to collect, filter, group, and analyze findings from previous studies in a systematic and structured manner. The study adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol as a guideline to plan, execute, and comprehensively report systematic reviews and meta-analyses [66, 67]. PRISMA has been widely applied across various disciplines, including health [68], electrical engineering [69] and informatics [70-72]. This methodological approach offers several advantages, such as selecting high-quality articles, evaluating the strengths and weaknesses of studies, grouping relevant literature, and narrowing down the article pool to a manageable set for analysis. Systematically, this method comprises five main stages: (1) defining the topic, (2) formulating research questions (RQs), (3) establishing inclusion and exclusion criteria, (4) screening and selecting studies, and (5) extracting data. An overview of these stages is presented in Figure 1.

Figure 1. Systematic review stage showing the main step from topic determination to data extraction

2.1 Determine the topic

The first stage in a SLR is to determine a research topic that is clear, relevant, and offers significant contributions. The topic should be grounded in current issues, identify research gaps, and have its potential practical and academic value. In this study, the research topic focuses on artificial intelligence-based eye-controlled virtual keyboard systems, with particular emphasis on biosignal-based approaches, namely electrooculography (EOG) and electroencephalography (EEG), as assistive interaction solutions for individuals with motor disabilities. Vision-based eye tracking studies are also included to provide a comparative perspective on the technology. Defining this topic helps narrow the scope of the review, ensures relevance to user needs, and provides a solid foundation for formulating RQs in subsequent stages.

2.2 Research Questions

At this stage, RQs were formulated based on the study objectives, specifically to summarize the available literature from previous studies using the Population, Intervention, Comparison, Outcome, and Context (PICOC) framework [66, 67]. The population consisted of individuals with motor disabilities. The intervention focused on the main components of the system under review, particularly the input and data acquisition processes. Comparisons were not addressed in this review. The outcome of interest was model accuracy in eye movement-based systems. Regarding context, the review considered articles published in journals and conference proceedings within the fields of computer science, health, electrical engineering, and informatics. The following RQs were formulated:

1. RQ1: What approaches, including AI and non-AI, are used in eye-controlled virtual keyboard systems?
2. RQ2: How do eye-controlled virtual keyboard systems receive input from eye movements through different acquisition modalities (biosignal-based and vision-based technologies)?
3. RQ3: What datasets were used, and what were the characteristics of the test participants?
4. RQ4: What metrics were used to evaluate the performance of eye-controlled virtual keyboard systems?
5. RQ5: What are the main challenges in developing AI-based eye-controlled virtual keyboard systems for people with motor disabilities?

6. RQ6: What are the recommended future research directions to support the development of AI-based eye-controlled virtual keyboard systems?

2.3 Inclusion and exclusion criteria

This stage was conducted after the RQs were formulated to ensure that the study selection criteria aligned with the research focus and objectives. Inclusion and exclusion criteria were established to ensure that only relevant and high-quality studies were included in the SLR, thereby maintaining a focused, consistent, and valid scope. This review included studies employing both biosignal-based and vision-based eye movement acquisition methods. Vision-based approaches served as a baseline for comparison to provide context for technological developments, while biosignal-based methods were analyzed in more depth due to their relevance to users with severe motor disabilities and limited motor control.

Table 1. Inclusion and exclusion criteria for literature selection: Population, Intervention, Comparison, Outcome, and Context (PICOC)

Component	Inclusion Criteria	Exclusion Criteria
Participants (RQ3)	Studies involving individuals with physical motor disabilities or healthy participants acting as proxies in testing eye-controlled virtual keyboard systems.	Studies involving participants outside the context of eye-controlled communication.
Intervention (RQ1 and RQ2)	Eye-controlled virtual keyboard systems utilize diverse input modalities, including biosignal-based approaches such as electrooculography (EOG) and electroencephalography (EEG), as well as vision-based systems such as eye-tracking or camera-based interaction, implemented using either AI-based or conventional approaches.	Not eye movement input.
Comparison	Not Applicable (N/A)	Not Applicable (N/A)
Outcome (RQ4, RQ5, RQ6)	Studies reporting quantifiable metrics such as classification accuracy, input speed, usability scores, or technical challenges and future research agendas	Studies providing only subjective opinions without qualitative or quantitative data validation.
Context (RQ2 and RQ3)	Peer-reviewed journals and conference proceedings published in the fields of computer science, health, informatics, and electrical engineering.	Grey literature, including theses, internal institutional reports, preprints, and non-peer-reviewed articles.

Based on these criteria, a literature search strategy was subsequently designed to identify suitable studies. All inclusion and exclusion criteria were developed using the PICOC framework, which is summarized in Table 1.

2.4 Study screening and selection

The article selection process followed the PRISMA flowchart, which is divided into three stages: identification, screening, and inclusion. In the identification stage, a comprehensive literature search was conducted by identifying relevant sources, grouping the literature by database, and applying several keyword variations over the past five years. The initial search used general keywords, such as "virtual keyboard AND electrooculography (EOG)". This search yielded 5,391 results in ScienceDirect, 410 in IEEE Xplore, and 2,870 in Google Scholar; however, many of these were not relevant to the context of this study. Next, the keywords were expanded by adding terms related to eye blink and eye movement, focusing on research that uses eye movements as control input. This stage resulted in an even higher number of articles, specifically, 613,110 in ScienceDirect, 4,868 in IEEE Xplore, and 13,800 in Google Scholar, making it increasingly difficult to conduct an in-depth review. To filter articles and make them more relevant to the research topic, the terms "disability" and "artificial intelligence" were added. This strategy successfully reduced the number of articles to 939 in ScienceDirect, 4,919 in IEEE Xplore, and 774 in Google Scholar.

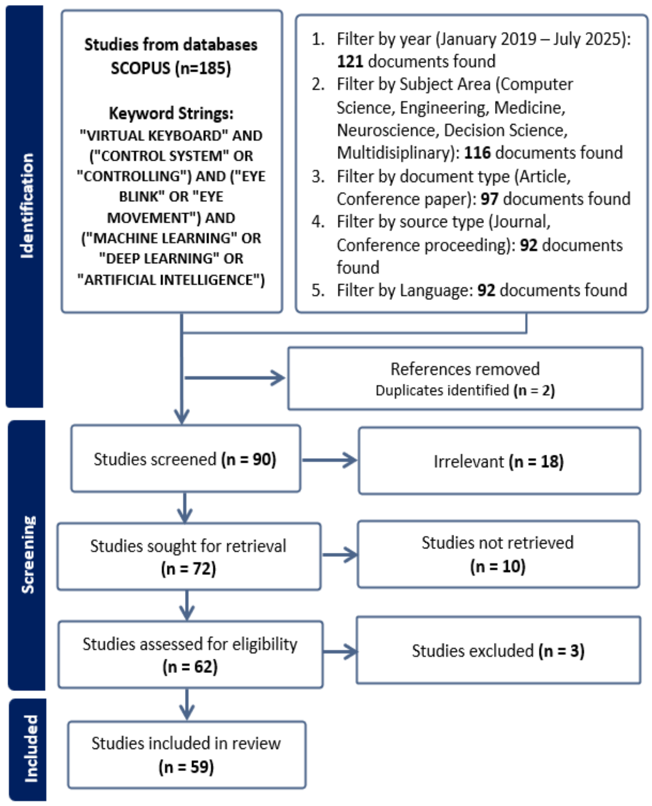

Figure 2. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram showing the study identification and selection process

Source: adapted from PRISMA 2020 statement [67]

Based on the keyword exploration results, a more systematic search string was developed by combining the main components: (1) virtual keyboard as the system focus, (2) control system or controlling as the function context, (3) eye blink or eye movement as the source of movement-based input, and (4) machine learning, deep learning, or artificial intelligence as the AI approach. Thus, the final search string used was: "VIRTUAL KEYBOARD" AND ("CONTROL SYSTEM" OR "CONTROLLING") AND ("EYE BLINK" OR "EYE MOVEMENT") AND ("MACHINE LEARNING"

OR "DEEP LEARNING" OR "ARTIFICIAL INTELLIGENCE"). This string was then applied to the Scopus database. The identification process yielded 185 documents relevant to the research keywords. This number indicates that the integration of artificial intelligence in eye-movement-based virtual control systems remains an emerging research area. After filtering by publication year (January 2019 – July 2025), the number of documents was reduced to 121. Further refinement within relevant fields of study, namely Computer Science, Engineering, Medicine, Neuroscience, Decision Sciences, and Multidisciplinary, resulted in 116 documents. Limiting the document types to articles and conference papers reduced the count to 97. After restricting sources to journals and conference proceedings, 92 documents were obtained. Applying language criteria retained 92 documents. From these, duplicates were removed, leaving 90 documents for the screening process. All articles were verified to be complete and fully readable. At the screening stage, 18 documents were excluded because they were deemed irrelevant to the research focus. Of the 72 retained documents, 10 were review articles that were not used at this stage but were set aside to strengthen the background information. Thus, 62 documents were thoroughly evaluated, and three were excluded for not meeting the eligibility criteria. Ultimately, a total of 59 documents were deemed eligible and included in this systematic review. Figure 2 presents the PRISMA flowchart illustrating the process flow from identification to screening and the final number of articles selected.

2.5 Data extraction

The data extraction phase was conducted on 59 studies that met the inclusion criteria. An initial thematic analysis was performed using SciSpace to identify findings relevant to the RQs. Next, all articles were thoroughly reviewed and manually extracted to obtain comprehensive data covering technological approaches (AI and non-AI), input modalities, dataset and participant characteristics, performance metrics, and a critical analysis of research challenges. All references were managed using Mendeley, while the extraction results were systematically compiled in Microsoft Excel. To improve readability and facilitate the identification of technical patterns, the extracted data is organized into three thematic tables. Table 2 provides a technical mapping of input modalities, acquisition hardware, and AI architectures published between 2019 and 2025. Table 3 presents a summary of dataset characteristics, participant demographics, and corresponding system performance to evaluate the validity coverage of existing experimental designs. Finally, Table 4 offers a synthesis of identified research gaps, technical challenges, and physiological barriers encountered in eye-controlled systems, providing a critical overview of the current state of the art.

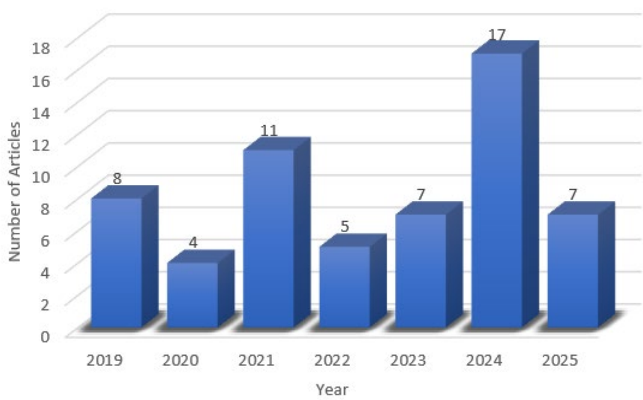

Figure 3. Annual number of publications from 2019 to 2025

The distribution of the 59 selected articles by publication year is presented in Figure 3. The trend shows a significant increase over the past five years (2019–2025), with a peak of 17 publications in 2024. Despite fluctuations between 2020 and 2022, the number of publications has been increasing since 2023 and is predicted to continue to increase until the end of 2025. This positive development reflects the intensive research interest in integrating artificial intelligence with eye movement-based control systems to support independent interaction for people with motor disabilities.

Table 2. Technical mapping of input modalities, acquisition hardware, and AI architectures (2019–2025)

Year	Ref.	Input Modality	Acquisition Method / Hardware	AI System / Approach	Specific Algorithm
2019	[2]	Gaze tracking	Infrared Tracker (Eye Tribe 1.0 / Tobii Pro)	Non-AI	Biological Signal Translator Module (Rule-based gaze mapping)
2020	[9]	Biosignal (EOG)	5-ch electrodes, ADT26 bio amplifier (100 Hz)	DL	TDNN (Time Delay Neural Network) with Band Power Features
2019	[16]	Biosignal (EOG)	Ag/AgCl electrodes, AD-620 amp, NI USB-6008 DAQ	Non-AI	DTCL (Dynamic Threshold Control Logic) with training-based thresholding
2019	[35]	Biosignal (EEG)	NeuroSky Mindwave (FP1: Frontal Pole 1 / left forehead + Ear clip reference, 512 Hz)	Non-AI	State-machine (Divide & Conquer with 1-5 blink commands)
2019	[54]	Biosignal (EOG)	Custom EOG Mindo device, 4-ch electrodes, INA2126 amp, 256 Hz	ML	Peak Detection & Pattern Recognition with slope variation
2019	[55]	Biosignal (EOG)	5-ch electrodes, ADT26 bio amplifier (100 Hz), HHT (Hilbert Huang Transform) feature extraction	DL	PRNN (Pattern Recognition Neural Network) with Levenberg-Marquardt
2019	[56]	Biosignal (EOG)	5 Ag/AgCl electrodes, AD Instruments, EMCD, PCA, GHM multi-wavelet	DL/ML	GWO-NN (Grey Wolf Opt. - Neural Network)
2019	[61]	Biosignal (EEG/Hybrid)	Emotiv EPOC+ (14 EEG sensors, 9-axis motion sensor, 128 Hz)	ML	Feature-based Translation (facial expressions + head movements)
2020	[34]	Biosignal (EEG)	AF3 & AF4 sensors, notch filter 60 Hz, band-pass filter	DL	MLP (Multi-Layer Perceptron) with 5 layers [50,100,150,100,50]

Year	Ref.	Input Modality	Acquisition Method / Hardware	AI System / Approach	Specific Algorithm
2020	[46]	Biosignal (EOG)	5 Ag/AgCl electrodes, AD Instruments, EMCD, PCA, GHM multi-wavelet	DL/ML	GWO-NN (Grey Wolf Optimization with Nearest Neighbor classifier)
2020	[47]	Biosignal (EOG)	5 Ag/AgCl electrodes, AD Instruments, EMCD, PCA, multi-wavelet transform	DL	NN (Neural Network) with Levenberg-Marquardt training
2020	[60]	Biosignal (EEG)	OpenBCI, Fp1 & Fp2 electrodes (250 Hz), Butterworth filter 1-30 Hz	Non-AI	RVEB (Recognizing Voluntary Eye Blinks) - threshold-based
2021	[6]	Biosignal (EOG)	ADInstruments T26 bioamplifier, 5-ch electrodes, 100 Hz, notch 50 Hz	DL	PNN (Probabilistic Neural Network)
2022	[7]	Biosignal (EOG)	ADIT26 LabChart, 5 gold-plated electrodes, Periodogram (FFT), 100 Hz	DL	FFNN (Feed-Forward NN) with ALO (Ant Lion Optimization)
2021	[18]	Biosignal (EOG)	Wearable glasses, 4 dry electrodes, INA2126 amp, MSP430, 256 Hz	Non-AI	DSP & Thresholding with feature coding (-2 to +2)
2021	[24]	Hybrid (Gaze-Finger)	Gaze-supervised proofreading & typing on Samsung Galaxy S6	DL	DQN (Deep Q-Network) with hierarchical RL (4 agents)
2021	[25]	Biosignal (EEG)	Mindwave Mobile 2, ThinkGear TGAM1, single electrode (512 Hz), 60 Hz notch	DL	2-layer LSTM with Dropou
2021	[26]	Biosignal (EOG)	Graphene textile electrodes, INA122 amp, Butterworth 0.5-10 Hz, Bluetooth HC06	Non-AI	Configuration-based (Fast/Slow/Blink) pattern detection
2021	[29]	Biosignal (EEG)	NeuroSky Mindwave (Attention/Meditation)	DL	ANN (Kohonen Self-Organizing Map) competitive learning
2021	[39]	Gaze tracking	Tobii Pro X2-30 (30 Hz, 0.32° accuracy), 14" laptop	Non-AI	Ergonomic & Statistical Analysis (ANOVA)
2021	[48]	Biosignal (EOG)	g.tec gUSBamp (256 Hz), 50 Hz notch, Signal-to-RGB Image	DL	CNN (Convolutional Neural Network) + EUDN + Modified Q-Learning RL
2021	[62]	Biosignal (EEG)	Mindwave Mobile (FP1 + A1 earlobe), TGAM1 chip, 512 Hz	Non-AI	Threshold Detection with 3s dwell time
2021	[63]	Biosignal (EEG)	NeuroSky Mindwave (FP1 + ear clip), 512 Hz, attention index (1 Hz)	DL/ML	Neural Signal Analysis with FSM, Fitts' model
2022	[10]	Hybrid (Gaze, Head, Voice)	MPU6050 (Head), QTR-1A (Eye), Voice Module	DL	ANN (Artificial Neural Network), 2-layer: 10 + 4 neurons with EMA filter
2022	[19]	Hybrid (EOG + sEMG)	3 EOG electrodes + facial sEMG (1000 Hz)	Non-AI	Thresholding & Control Logic
2022	[27]	Gaze tracking	Tobii 4C (90Hz), 23" monitor, 50-60 cm distance	Non-AI	Smooth Pursuit Matching Algorithm
2022	[30]	Biosignal (EOG)	5-ch electrodes, CPSD Feature Extraction	DL	CNN (Convolutional Neural Network) with convolution, pooling, ReLU, fully connected layers
2022	[31]	Hybrid (EEG, Gyro)	Custom EEG with 3 dry electrodes (FP1, F7, A2), MPU-6050 gyro, 125 Hz	ML	SVM (Support Vector Machine) with 6 features (Welch PSD, Eα/Eβ ratio)
2023	[3]	Computer vision	Dlib 68 facial landmark + OpenCV, webcam (30 fps), 40-45 cm	Non-AI	EAR (Eye Aspect Ratio) Calculation with 5-point calibration
2023	[13]	Computer vision	Smartphone front camera, MediaPipe Face Mesh	ML	Face & Eye Detection with Blink Calculation
2023	[20]	Computer vision	Webcam (5 MP), Raspberry Pi 3, OpenCV, Dlib, 30 cm	Non-AI	Dlib & OpenCV EAR and pixel ratio gaze tracking
2023	[36]	Biosignal (EOG)	5 Ag/AgCl electrodes, 256 Hz sampling, bio-signal amplifier	DL	RNN with GRU (32) + Bi-GRU (32) + 2 dense layers
2023	[44]	Gaze tracking	Tobii 4C (90 Hz), 27" monitor, Unity + Tobii API	Non-AI	EyeCompass (Damping brush mechanism)
2023	[57]	Biosignal (EEG)	Mindwave Neurosky + FPGA (HC-05 BT)	Non-AI	Differentiator & Low-pass Filter with threshold
2023	[58]	Biosignal (EEG)	NeuroSky MindWave (512 Hz, FP1)	Non-AI	Cross-Correlation Method with binary coding
2024	[4]	Hybrid (EOG, ECG, PPG)	Nexus-10MKII (256 Hz), Headband integration	DL	LSTM (Long Short-Term Memory)
2024	[5]	Biosignal (EOG)	4 electrodes, NI USB-6008 DAQ, filter/amp circuit, Arduino Uno	ML	SVM (Support Vector Machine), one-vs-one with 6 hyperplanes
2024	[11]	Computer vision	Webcam (30 fps), MediaPipe Iris + Face Mesh, 25-60 cm	Non-AI	Iris Coordinate Mapping with distance scaling
2024	[12]	Computer vision	Webcam, MediaPipe Face Mesh, OpenCV, RGB processing	Non-AI	MediaPipe Face Mesh with iris tracking and blink detection
2024	[21]	Gaze tracking	Tobii 4C (90 Hz), webcam, Affectiva SDK, 15" laptop	DL	CNN (Convolutional Neural Network) with gaze locking + blink trigger (650 ms)
2024	[22]	Computer vision	Camera, Raspberry Pi, LCD, Hough Circle, OpenCV	DL	Parallel-CNN (Parallel Convolutional Neural Network)
2024	[23]	Gaze tracking	Tobii Pro X3-120, Kinect (60 fps), Tobii Unity SDK	Non-AI	PERCLOS Algorithm (threshold 85)

Year	Ref.	Input Modality	Acquisition Method / Hardware	AI System / Approach	Specific Algorithm
2024	[28]	Gaze tracking	Tobii Eye Tracker 5 (33 Hz), PCCR method, TobiiPro.SDK	DL	DCC (Dilated Causal Convolutional Network) with TCN
2024	[32]	Computer vision	Camera, Raspberry Pi, LCD, OpenCV, MediaPipe, PyAutoGUI	ML	SVM (Support Vector Machine) with accuracy 95%
2024	[33]	Biosignal (EOG)	3 Ag/AgCl electrodes, BioAmp EXG Pill, DRL circuit, bandpass 1.59-3.39 Hz	Non-AI	Thresholding Algorithm with FSM for UAV control
2024	[37]	Vision (AR Gaze)	HoloLens 2 AR HMD, TOF sensors, eye tracking, OpenXR, MRTK	ML	Bayesian Prediction Algorithm with gaze and language model
2024	[38]	Gaze tracking	Arrington Research (3 Cameras + 3 IR LEDs)	Non-AI	Threshold-based Fixation Time (1.5-2 s dwell)
2024	[40]	Gaze tracking	Tobii 5, 24" monitor, Unity, Tobii SDK	Non-AI	Euclidean Algorithm (Smooth Pursuit)
2024	[42]	Gaze tracking	Gazepoint GP3 HD (150Hz)	Non-AI	Linear Smooth Pursuit with n-gram Prediction
2024	[43]	Computer vision	Webcam, OpenCV, MediaPipe, Haar Cascade, HSV, Tkinter GUI	DL	CNN & DNN for hand/eye gesture recognition
2024	[45]	Computer vision	Webcam (30 fps, 720p), Haar Cascade, Split-HSV method	DL	Eyenet (Di-eyeNET) custom CNN, 2 blocks
2024	[49]	Biosignal (EOG)	g.tec g.USBamp (256 Hz), 6 Ag/AgCl electrodes, bandpass 0-30 Hz, notch 50 Hz	ML	HMM (Hidden Markov Model) with bearing angle features (36 levels, 10° discretization)
2025	[8]	Biosignal (EOG)	ITO film electrodes on glasses, OPA129 amp, capacitive coupling, BPF 0.05-35 Hz	DL	Hierarchical CNN with FFT/Band Power/HHT features
2025	[41]	Gaze tracking	Tobii Pro Nano (60 Hz), 27" screen, Python Tkinter, 45-85 cm	Non-AI	Dwell-time method (1000ms)
2025	[50]	Biosignal (EOG)	2×100 tensor (HEOG/VEOG), 5 public datasets, downsampled to 100 Hz	DL	MIDF-NET (Multi-scale DL) with 2 Inception modules + MSFF fusion
2025	[51]	Biosignal (EOG)	3 electrodes, ADS1292R (24-bit ADC), STM32F4, STFT, 125 SPS	DL	Time-Frequency YOLOv3 with four-channel backbone
2025	[52]	Biosignal (EOG)	5 Ag/AgCl electrodes, ESP32 (12-bit ADC, 250 Hz), Raspberry Pi, Butterworth BPF 0.5-40 Hz	ML	SVM (Support Vector Machine) with 6 features (peaks + peak gaps)
2025	[53]	Biosignal (EOG)	JINS MEME ES_R glasses, 50 Hz, BLE, 3-axis accelerometer, Butterworth BPF 0.25-7.5 Hz	ML	Random Forest (Lasso selection)
2025	[59]	Biosignal (EEG)	3D VR Environment, Deep Encoder	DL	DL Encoder (PoR Prediction)

Table 3. Summary of dataset characteristics, participant demographics, and corresponding system performance

Year	Ref.	Dataset Source	Participant Type	Count	Detailed Profile	Key Performance Results
2019	[2]	Private	Mixed	30	29 Healthy, 1 Disabled (17-40y)	SUS: 89.9 (H), 92.5 (D)
2019	[9]	Private	Healthy	20	20 Healthy (21-35y)	Accuracy: 91.55%
2019	[16]	Private	Healthy	10	10 Healthy (22-30y)	Success Rate: 100%
2019	[35]	Private	Healthy	Not Spec.	Proof-of-concept	Real-time Functionality
2019	[54]	Private	Not Spec.	Not Spec.	Not specified	Accuracy: 80% - 100%
2019	[55]	Private	Healthy	20	20 Healthy (10M, 10F, 20-44y)	Accuracy: 94.60%
2019	[56]	Private	Not Spec.	3	Not specified	Max Accuracy: 88%
2019	[61]	Private	Mixed	18	8 Disabled (Men), 10 Healthy (22-25y)	Disabled users scored higher than healthy users
2020	[34]	Private	Healthy	15	15 Healthy (10M, 5F, 20-31y)	Robot Accuracy: 91.7%, PPV: 0.814
2020	[46]	Private	Not Spec.	3	Not specified (Conditions unknown)	Avg. Accuracy: 94%, F1-score: 93-95%
2020	[47]	Private	Not Spec.	3	Not specified (Conditions unknown)	Right eye move accuracy +8% to 26%
2020	[60]	Private	Healthy	12	12 Healthy (21-34y)	Avg. Accuracy: 95%, Command time: 2.04s
2021	[6]	Private	Mixed	15	Young (20-25y), Old (45-55y), ALS (35-50y)	Accuracy: 94% (Young), 90.37% (ALS)
2021	[7]	Private	Healthy	10	10 Healthy (20-30y)	Online Accuracy: 90.12%, Robot control: 98.12%
2021	[18]	Private	Healthy	6	6 Healthy Men (20-28y)	Avg. Accuracy: 87.67%
2021	[24]	Private	Not Spec.	30	30 Participants (Conditions unknown)	Typing Speed: Δ 1.97 WPM from human
2021	[25]	Private	Not Spec.	8	8 Participants (20-75y)	Model Acc: 92%, Spelling Prec: 91.26%
2021	[26]	Private	Not Spec.	5	5 Participants (Conditions unknown)	6 CPM, 100% Acc (Typing)
2021	[29]	Private	Not Spec.	9	9 Participants (20-65y)	Max Acc: 95%, Min Acc: 50%
2021	[39]	Private	Healthy	20	20 Healthy (10M, 10F, 21-25y)	Accuracy: ~95%; Optimal spacing: 75 px

Year	Ref.	Dataset Source	Participant Type	Count	Detailed Profile	Key Performance Results
2021	[48]	Private	Healthy	11	11 Healthy (Avg. age 27.7y)	Global Accuracy: 87.73%
2021	[62]	Private	Not Spec.	7	7 Participants (Conditions unknown)	25% faster typing with Priority layout
2021	[63]	Private	Healthy	20	20 Healthy (14M, 6F)	Single blink accuracy: 98%
2022	[10]	Private	Disabled	2	2 Disabled (19y & 45y)	Head: 93.3% (A), 86.6% (B); Voice: ~65%
2022	[19]	Private	Healthy	9	9 Healthy (4M, 5F, 20-25y)	EOG Acc: 92.04%; sEMG Acc: 96.10%
2022	[27]	Private	Healthy	32	32 Healthy (19M, 13F, 19-71y)	Error Rate ≈ 0; KSPC ≈ 1.03
2022	[30]	Private	Healthy	8	8 Left-handed (4 Trained, 4 Untrained)	Acc: 93.51% (Trained), 86.88% (Untrained)
2022	[31]	Private	Healthy	9	9 Healthy (Real-time testing)	Accuracy: 96.65%; Error rate: 0.89/min
2023	[3]	Private	Mixed	30	19 Healthy, 11 Disabled (ALS & Glasses, 15-60y)	Blink Acc: 97.66%; Typing: 15-20 CPM
2023	[13]	Private	Healthy	10	10 Healthy (21-32y)	Acc: 94% (Holder), 91% (Handheld)
2023	[20]	Private	Not Spec.	Not Spec.	Not specified	Dlib Acc: 94.5%; OpenCV Acc: 92.9%
2023	[36]	Private	Healthy	6	6 Healthy (Extensive trials: 1500 events)	Acc: 99.77%; F1-Score: 99.77%
2023	[44]	Private	Mixed	161	150 Healthy (Swe, Chi), 11 Disabled (Stroke, ALS, CP)	Error Rate: 0.274 (Gaze) vs 0.098 (Touch)
2023	[57]	Private	Not Spec.	Not Spec.	Lab setting (Intentional blinking)	FPGA Error: 5%; NeuroSky Error: 30%
2023	[58]	Private	Healthy	20	20 Healthy (20-55y)	System Accuracy: 98.75%
2024	[4]	Private	Not Spec.	3	General participants	Improved Signal Stability (Ag/AgCl vs Headband)
2024	[5]	Private	Healthy	7	7 Healthy participants	Accuracy: 99%, Real-time Success: 92.5%
2024	[11]	Private	Mixed	30	10 Disabled (8M, 2F), 20 Non-disabled (12M, 8F)	Typing: 15.8 CPM (D), 21.7 CPM (ND); SUS: 90.6
2024	[12]	Private	Not Spec.	Not Spec.	Not specified	Qualitative: Precise & Responsive control
2024	[21]	Private	Healthy	20	20 Participants (23-28y, Postgraduate)	Max Success: Lock range at 21.074° angle
2024	[22]	Private	Disabled	4	4 Children (Severe motor & communication difficulties)	Real-time Gaze & Cursor Estimation
2024	[23]	Private	Healthy	20	20 Healthy (Postgrad students, 23-28y)	Success Rate: 96.65% (2 blinks)
2024	[28]	Private + Public	Healthy	26	20 Private (26-46y), 6 Public participants	Private Acc: 96.2%; Public (HideMyGaze): 98.81%
2024	[32]	Private	Not Spec.	20	20 Participants (Conditions unknown)	Acc: 95% (Front-light) vs 50% (Side-low light)
2024	[33]	Private	Not Spec.	Not Spec.	Not specified (UAV Control context)	Qualitative: Precise & Consistent UAV control
2024	[37]	Private	Healthy	38	38 Healthy (25M, 13F)	Error rate ↓ 43.05% vs gaze alone
2024	[38]	Private	Not Spec.	Not Spec.	Not specified	Qualitative: Writing message in ~4 mins
2024	[40]	Private	Healthy	20	20 Healthy (20-26y)	Completion Rate: 96% (Circular & Rect.)
2024	[42]	Private	Mixed	31	31 Participants (16-73y, many with glasses)	Avg. 1.32 WPM (Sentences); 2.75 WPM (Digits)
2024	[43]	Not Spec.	Not Spec.	Not Spec.	Not specified (Hand & Eye integration)	Accuracy: 96.5% (CNN Hand); 95.7% (DNN Eye)
2024	[45]	Public + Private	Healthy	61	55 Public (SBVPI), 6 Private (Mixed ages)	Accuracy: 90%, Min. Training Time
2024	[49]	Private	Healthy	10	10 Healthy (Avg. 22.8y)	Top-5 rate >80% for word patterns
2025	[8]	Private	Healthy	9	9 Healthy (20s, 6M/3F)	Accuracy: 84% (Vert), 90% (Horiz)
2025	[41]	Private	Healthy	40	40 Healthy (20M/20W, Avg 24y)	Success Rate: 100% (Red dot activation)
2025	[50]	Public	Healthy	50	50 Subjects (59 Recordings)	Avg. Accuracy: 92.16% (across 5 datasets)
2025	[51]	Private	Healthy	6	6 Healthy (2W/4M)	Accuracy: 97.60% (Proposed system)
2025	[52]	Private	Healthy	15	15 Healthy (10W/5M, 20-30y)	Accuracy: 100% (SVM Classification)
2025	[53]	Private	Healthy	12	12 Healthy (6M/6W, 22-39y)	Accuracy: 85.8% (Stress/Fatigue detect)
2025	[59]	Private	Healthy	5	5 Healthy (2W/3M, 21-29y)	Avg. Accuracy: 80.1% (3D Gaze)

Table 4. Synthesis of identified research gaps, technical challenges, and physiological barriers in eye-controlled systems

Challenge Theme	In-depth Research Gap Analysis	References
Data Generalization & Population Bias	Existing models are primarily trained on small, private datasets ($N < 15$) featuring healthy participants. This creates significant population bias, limiting the system's validity when applied to elderly users or individuals with motor disabilities who exhibit distinct oculomotor patterns.	[2, 8-10, 16, 18, 25, 29, 30, 35, 36, 40, 42, 45, 48, 49, 51, 53, 55, 59]
Environmental Robustness & Luminance	Vision-based systems (webcams or eye-trackers) remain highly sensitive to fluctuations in light intensity, infrared reflections from eyeglasses, and head posture instability. These vulnerabilities significantly reduce system reliability outside strictly controlled laboratory environments.	[2, 3, 11-13, 20-23, 29, 32, 33, 43, 45]
Signal Stability & Artifact Interference	For biosignal-based modalities, electrooculography (EOG) and electroencephalography (EEG), the primary challenges include baseline drift and signal contamination from facial muscle activity (electromyography (EMG) artifacts). Environmental noise and electromagnetic interference from surrounding electronics often degrade the signal-to-noise ratio	[4, 5, 7, 18, 34, 36, 50, 51, 54, 55, 60, 61]
Inter-subject Variability	Significant inter-individual variability in eye movement patterns and signal amplitudes renders static thresholding ineffective. Consequently, systems often require tedious and time-consuming recalibration for each new user to maintain accuracy.	[19, 24, 28, 30, 42, 52]
Ergonomics & Visual Fatigue	Users frequently encounter the "Midas touch" problem (unintentional selections) and eye fatigue or muscle strain from prolonged use. Additionally, the reliance on wet (gel-based) electrodes can cause discomfort and skin irritation in daily, long-term applications.	[2, 3, 19, 23, 30, 31, 39, 41, 44, 58]
Latency & Real-time Constraints	A notable performance gap exists between offline dataset results and real-time online testing. Complex deep learning architectures often demand high computational resources, leading to execution latency when deployed on resource-constrained embedded devices.	[4, 7, 37, 40, 47, 52, 55-57]

3. RESULTS AND DISCUSSIONS

3.1 AI approaches and technical mapping for eye-controlled virtual keyboard

Based on a review of 59 studies, 61% of eye-controlled virtual keyboard systems have now transitioned to using Artificial Intelligence (AI), employing either Machine Learning or Deep Learning methods. As illustrated in Figure 4, this key trend indicates a marked shift from conventional rule-based methods (17%) and non-AI vision approaches (22%) toward systems capable of autonomous pattern recognition. The underlying reason for this shift is AI's superiority in processing eye signals, which are often nonlinear and noisy, a technical challenge that has been difficult to overcome using traditional thresholding methods alone.

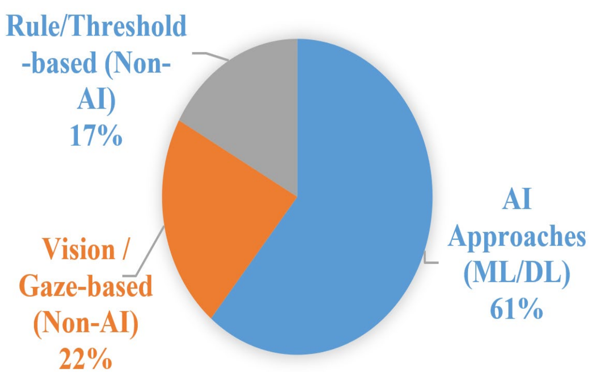

Figure 4. Distribution of approaches used in the eye-controlled virtual keyboard systems

3.1.1 Model evolution: rationalizing architecture selection

The technical mapping in Table 2 shows the evolutionary trajectory across three main phases:

1) Classical ML for efficiency (2019–2020): In the early stages, research relied heavily on architectures such as Time Delay Neural Networks (TDNN) and Artificial Neural Networks (ANN). These models were chosen for their stability and low computational resource requirements. For example, Tang et al. [9] used a TDNN to classify nine gaze directions with 91–92% accuracy, while Martinez-Ledezma et al. [34] applied an MLP-based ANN to recognize eye-blink patterns.

2) Deep Learning for adaptive representation (2021–2023): Subsequently, the field shifted strategically toward the use of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. CNNs are adopted to automate spatial feature extraction in vision-based systems, while LSTMs, as demonstrated by Reyes et al. [25], are used to capture temporal dependencies in EEG/EOG signals. This transition aims to minimize the need for complex manual feature engineering. The technical rationale for the dominance of CNNs over RNNs and traditional ML models lies in their structural efficiency for spatial hierarchical mapping. CNNs are uniquely capable of identifying eye-movement signatures, such as blink spikes or saccade directions, within noisy signal streams through weight-sharing, which significantly reduces the computational footprint during inference compared to LSTMs. This provides a crucial performance trade-off: while LSTMs are better at capturing long-term temporal dependencies, CNNs offer the millisecond-level responsiveness essential for a fluid, real-time typing experience.

3) Hybridization and metaheuristic optimization (2023–2025): Recent studies have begun to focus on integrating Deep Learning with metaheuristic optimizers to balance precision and real-time execution speed. Examples include Zeng et al.'s MIDF-NET [50] and Son et al.'s hierarchical CNN [8], which achieved high accuracy, up to 92.16%, through multi-scale signal derivative processing. Furthermore, hybrid systems, such as the Tobii DCNN [28] and YOLOv3 [51], combine real-time processing capabilities with optimized model depth.

3.1.2 Performance trade-offs and modality integration

The data in Table 2 highlight a crucial technical trade-off: while deeper models like CNNs can offer superior accuracy, they pose significant latency challenges on embedded hardware. Conversely, simpler ML models remain a relevant option for portable systems due to their lower power consumption. Ultimately, the convergence of these various AI approaches facilitates the integration of multiple modalities, such as EOG, EEG, and vision, to provide a more responsive and layered input system for users with motor disabilities.

3.2 Classification and distribution of input modalities

Based on a review of 59 studies summarized in Table 2, the choice of input modality is determined by the balance between signal precision and user comfort. The data distribution in Figure 5 confirms the dominance of biological signals over vision-based techniques in virtual keyboard development.

3.2.1 Biological signals: EOG Stability and EEG complexity

Biosignal-based systems are the most widely explored category in the literature, encompassing 36 articles, divided into two main modalities: EOG and EEG.

1) EOG dominance (22 pure articles and 2 hybrid)

EOG is the most dominant modality due to its ability to directly record the eye's electrical activity with a high Signal-to-Noise Ratio (SNR). The technical rationale for using EOG lies in its reliability in detecting eye movement directions in up to nine directions through the placement of three to six electrodes. Critical analysis suggests a shift in algorithms from static thresholding to CNN [8, 30] and RNN [36] models to address inter-individual signal variability. The main drawback of EOG is its invasiveness; however, recent trends are beginning to address this through wearable devices such as the JINS MEME smartglasses [53] or microcontroller-based wireless systems [18, 52]. Additionally, two studies adopted a hybrid EOG-based approach, combining it with sEMG for enhanced muscle control [19] and physiological ECG/PPG signals [4]. This approach aims to improve system reliability against inter-user variability and environmental disturbances that often occur in biosignal-based assistive applications.

2) EEG potential (10 pure and 2 hybrid)

EEG was used in 10 studies as a single modality to capture users' cognitive intentions and attention levels, typically through wireless devices such as the NeuroSky MindWave [29, 35, 58, 63]. While offering the potential for deeper cognitive engagement, EEG faces significant challenges due to its high sensitivity to facial muscle artifacts and non-neural noise, necessitating adaptive models such as ANNs and LSTM networks to maintain stability and classification accuracy [4, 25, 34]. Two hybrid studies with EEG were found, namely the integration of EEG and EOG in one hybrid framework [31], the integration of EEG with motion sensors and facial expression detection [61], which confirms that this biosignal fusion is still relatively unexplored despite having high complementary potential.

3.2.2 Eye tracking and computer vision technologies: Accessibility vs. robustness

1) Hardware-based gaze tracking (14 articles).

This group relies on active infrared sensors and the Pupil Center Corneal Reflection (PCCR) principle, as implemented in Tobii, Gazepoint, and Arrington Research devices [2, 23, 28, 38, 40, 41]. The primary focus of this approach is the precise mapping of gaze coordinates (*x, y*) for direct cursor navigation. However, this approach is susceptible to the Midas Touch phenomenon, requiring additional validation mechanisms such as dwell time, smooth pursuit, or time-series-based prediction [40-42]. This category also includes Augmented Reality (AR) integration via HoloLens 2 [37], fixation monitoring, and gaze-based supervised typing systems.

2) Standard camera-based computer vision (9 articles).

This approach is non-invasive and leverages standard RGB cameras on webcams or smartphones to increase accessibility and reduce hardware costs [11, 13, 45]. The technical focus is on detecting facial landmarks using libraries such as MediaPipe, Dlib, or OpenCV, with algorithms such as the Eye Aspect Ratio (EAR) used to extract eye actions, particularly blinks, as input triggers [3]. While easy to implement, standard camera-based systems exhibit lower robustness to variations in lighting and head position than infrared sensor-based systems, often requiring additional preprocessing to maintain consistent performance.

This critical synthesis reveals a tension between the robustness and accessibility of existing modalities. EOG-based systems excel in temporal resolution and reliability in dark environments but are constrained by the physical invasiveness of electrodes. Conversely, vision-based systems offer high spatial precision for cursor navigation, but are susceptible to interference from lighting and head position. The lack of a “middle ground” solution that balances the stability of EOG with the practicality of RGB cameras represent a major gap in the development of truly adaptive assistive technology.

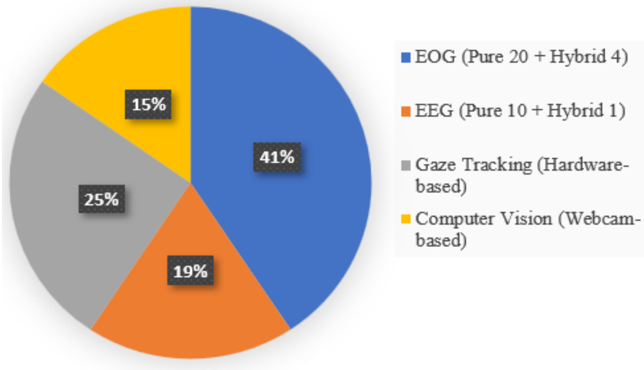

Figure 5. Input modalities and acquisition techniques

3.3 Dataset and participant

The characteristics of the datasets and test participants from 59 studies reveal a consistent pattern: 56 studies used private datasets from direct experiments, only one study used a public dataset [50], and 2 studies combined both [28, 45], utilizing datasets such as SBVPI and HideMyGaze. In terms of participants, healthy individuals dominate (49%), followed by studies that do not specify the participants' condition (41%), those with a mix of healthy participants and individuals with disabilities (8%), and finally, studies focusing exclusively on individuals with disabilities (2%). The number of participants ranges from 3 to 60, typically falling between 10 and 30, depending on the experimental design. The age range spans from 17 to 75 years, with a predominance of young adults (17–25 years), mostly students with normal vision, followed by adults (26–45 years), who are often involved in studies using EOG or eye-tracking systems. Older adults (46–75 years) appear only in studies involving individuals with motor disabilities such as ALS, stroke, or cerebral palsy [3, 5, 22, 44]. The distribution of test participants' conditions in eye-controlled virtual keyboard systems is illustrated in Figure 6.

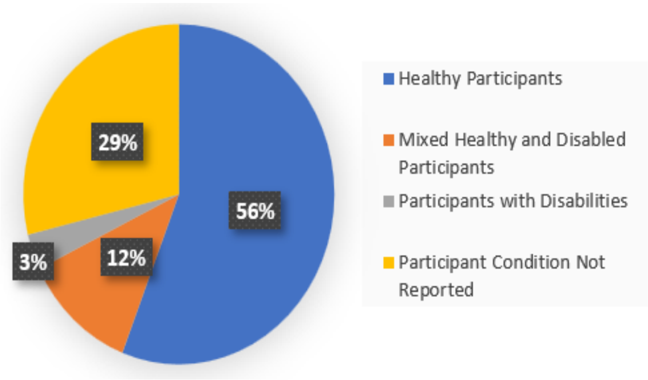

Figure 6. Percentage of participants' conditions involved in testing the eye-controlled virtual keyboard systems

In general, studies using private datasets and healthy participants focus on the development and validation of eye movement classification models, while studies involving participants with disabilities emphasize the implementation of virtual control systems and assistive interfaces. This pattern indicates that most studies are still at the proof-of-concept stage, with testing conducted under stable physiological conditions to ensure signal reliability and algorithm accuracy. Participants without disabilities produce low-noise signals and consistent movement patterns, which facilitate the calibration and training of models such as CNNs and SVMs. However, they introduce data bias due to differences in signal patterns, muscle fatigue, and cognitive responses in users with disabilities [73-75], which degrade model performance and limit the external validity of the system [75-77]. This observation aligns with Bissoli et al. [2], Lin et al. [18], and Qin et al. [59], who noted that most biological signal-based systems are still tested on small samples of healthy participants under controlled conditions. All three studies emphasize the need for further validation with users with disabilities and expansion to more heterogeneous test participant samples to address physiological biases, ensure safety, and enhance the clinical and social relevance of the developed systems.

From an ethical perspective, all research involving humans requires ethical approval to ensure participant safety and privacy [34]. However, limited access to disability communities and rehabilitation facilities constrains participant recruitment in this research area. As highlighted by recent research ethics reviews [78, 79], research involving individuals with disabilities must adhere to the principles of responsible inclusion. These principles include ensuring the accessibility of informed consent materials, adapting safe and equitable test procedures, and respecting participant autonomy. Moving forward, research should prioritize transitioning to the clinical stage through a co-design approach that directly involves users with disabilities. This requires strengthening cross-institutional collaboration among laboratories, hospitals, and disability communities, as well as establishing comprehensive ethics protocols and generating representative public datasets. This step will help ensure that the assistive technology developed is not only technically valid but also relevant and socially beneficial, in accordance with the recommendations of the *Global Report on Assistive Technology* [80].

3.4 The metrics evaluation

The eye-controlled virtual keyboard systems demonstrated high levels of accuracy and usability. Most studies reported accuracy values above 90%, indicating that methods utilizing EOG, EEG, and camera-based gaze tracking signals are capable of reliably recognizing gaze direction and eye blinks for use as control commands. In terms of usability, testing using the System Usability Scale (SUS) achieved a score of 89.9 for healthy users and 92.5 for users with disabilities [2]. This suggests that the system was perceived as easy to understand and comfortable to use by both groups. This finding is supported by another study, which reported a usability score of 90.6 for users with disabilities, with an average typing speed of 15.8 characters per minute (CPM) compared to 21.7 CPM for healthy users [11]. Notably, despite their slightly slower typing speed, users with disabilities reported higher comfort and satisfaction, underscoring the effectiveness of assistive technology in enhancing digital accessibility [61].

In terms of system performance, most models are able to recognize eye movements with an accuracy of 97–99% [5], achieving 100% precision for right and right-left movements and a real-time wheelchair control success rate of 92.5%. Other studies report accuracies of 94–96% [46] , with some reaching 99.7% for both vertical and horizontal channels [36]. A combined EOG and EEG system also demonstrates high performance, with an accuracy exceeding 92%, further confirming the effectiveness of a multimodal approach [51]. Interestingly, system performance remains relatively stable under varying usage conditions. For example, the accuracy rate remains high (91–94%) whether the smartphone is held in the hand or placed on a stand [13]. A significant decrease in accuracy (up to 50%) occurs only in dim lighting conditions and when the face is turned sideways [31]. In addition, the stability of the EOG signal was successfully improved through the use of headband electrodes, which reduced interference amplitude by up to 3.6 times on the vertical axis and 5.8 times on the horizontal axis, while increasing signal consistency by up to 12.1% [4].

Several studies have also evaluated system performance across various age groups and medical conditions. Average accuracy reached 94% in young adults, 93.27% in older adults, and 90.37% in patients with ALS [6], demonstrating the system's adaptability to diverse user characteristics. The integration of sEMG and EOG signals further improved command recognition accuracy to over 92% [19], while a hybrid BCI system achieved an accuracy of 96.65% ± 1.44% with an average response time of 2.65 seconds [31]. Other research has focused on functional efficiency and usability. Several studies report a 100% success rate for gaze-based activities [41], a 43.05% reduction in input errors compared to gaze-only methods [37], and a 25% increase in word selection efficiency on a priority-based keyboard layout compared to a traditional QWERTY keyboard [62]. Furthermore, single blinks have been shown to be the most stable form of input, with accuracy reaching 98% [63].

Overall, the results across various studies indicate that eye-controlled virtual keyboard systems have achieved an average accuracy of 90–99%, a response time of under three seconds, a very low error rate (ERR ≈ 0), and a usability score above 85. These findings reinforce that eye movement-based technology, whether utilizing EOG, EEG, or camera-based signals has reached a high level of technological maturity and is ready for broader testing in clinical contexts and assistive technology applications for individuals with motor disabilities.

3.5 Research gap

Based on the comparative synthesis presented in Tables 2-4, the current body of research on eye-controlled virtual keyboard systems exhibits clear empirical tendencies rather than a unified methodological consensus. One notable pattern is the frequent adoption of EOG as the primary input modality, often paired with machine learning or deep learning models, most commonly CNN-based architectures, due to their favourable balance between signal responsiveness and computational efficiency. However, this review indicates that this dominant configuration has not yet resolved several persistent and interrelated limitations.

A first research gap concerns limited generalizability arising from population bias and dataset constraints. Across modalities and algorithms, the majority of studies rely on small-scale, laboratory-based datasets involving predominantly young and healthy participants, with minimal inclusion of users with motor disabilities [2, 10, 11, 22, 44]. As reflected in Table 3, this limitation is not modality-specific but is shared by both biosignal-based and vision-based approaches. Consequently, performance metrics, particularly accuracy, should be interpreted cautiously, as they may not generalize to real-world assistive environments characterized by fatigue and user variability.

Second, the review reveals a misalignment between signal characteristics and model assumptions. Biosignal-based modalities such as EOG and EEG are inherently non-stationary and sensitive to artifacts, baseline drift, and electrode-related variability [4, 5, 18, 34, 51, 54, 55]. While CNNs and other deep learning models are increasingly used to improve feature extraction, most implementations implicitly assume short-term signal stability and are evaluated under controlled conditions. This creates a gap between algorithmic performance and sustained system reliability during prolonged interaction.

Third, as summarized in Table 4, robustness–usability trade-offs remain insufficiently addressed across modalities. Vision-based systems offer non-contact interaction but are highly vulnerable to environmental variability, head movement, and optical interference [2, 3, 11, 22, 45]. Conversely, biosignal-based systems provide stable temporal responsiveness but often compromise user comfort due to electrode placement and maintenance requirements. Despite these complementary strengths and weaknesses, most systems remain single-modality, limiting their ability to adapt to dynamic usage conditions.

A further gap emerges at the system level. High-performance models, whether based on CNNs, LSTMs, or hybrid architectures, are predominantly evaluated offline, with limited attention to real-time latency, embedded deployment, or long-term operational stability [4, 9, 23, 30, 37, 40, 46, 55, 56]. This disconnect constrains the practical translation of research prototypes into deployable assistive technologies. Finally, from a human–computer interaction perspective, issues such as visual fatigue, cognitive load, involuntary activation, and user discomfort are widely acknowledged but rarely integrated into model design or evaluation criteria [19, 23, 30, 39, 41, 44, 58] As reflected in Table 4, these factors play a critical role in real-world adoption yet remain secondary to accuracy-driven optimization. Taken together, these gaps indicate that the field's current limitations do not stem from the absence of effective sensing modalities or learning techniques. Rather, they arise from insufficient integration between empirical modality trends, adaptive modeling strategies, system-level constraints, and user-centered evaluation.

3.6 Discuss and recommendations

Based on the identified gaps, future research should focus on strengthening the integration and adaptability of existing approaches rather than prioritizing a single modality or algorithm family. A key agenda is the development of more representative and longitudinal datasets that encompass users with motor disabilities, diverse age groups, and long-term use sessions. This approach is crucial for enabling cross-subject and cross-condition validation as a more standardized and clinically meaningful evaluation practice [59]. To address the non-stationary nature of biosignals and the high inter-user variability observed across modalities, future systems must adopt adaptive learning mechanisms capable of handling temporal shifts and individual physiological differences. Techniques such as transfer learning, incremental adaptation, and lightweight reinforcement learning hold significant potential for supporting this goal without incurring excessive computational burden [33, 47, 48, 51, 52] Crucially, these approaches must be evaluated in continuous real-time operation, not merely in short-term experimental scenarios. Based on the synthesis of modality characteristics presented in Table 4, the development of a multimodal interaction framework represents a crucial research direction. Rather than replacing currently dominant approaches—such as EOG-based control or CNN-based classification—multimodal systems can leverage the complementary strengths of different modalities by dynamically adjusting the weights of sensor contributions in response to environmental conditions, signal degradation, or user fatigue [24, 29, 31, 42, 48, 53]. This strategy directly addresses the trade-off between system robustness and user comfort identified in this review.

At the system level, future research should explicitly incorporate implementation-oriented evaluation metrics, such as latency, energy consumption, calibration time, and hardware compatibility, particularly for embedded and wearable assistive platforms [4, 37, 40, 46, 55]. These metrics are essential for bridging the gap between experimental performance and the feasibility of real-world implementations. Finally, future research should elevate human-centered design to a level of importance equal to algorithmic accuracy. Adaptive interfaces that consider visual fatigue, cognitive load, and user comfort, combined with the development of dry electrodes and non-invasive sensors, represent key factors for sustainable use in everyday activities [19, 26, 39, 51, 52]. The integration of these systems into real-world assistive ecosystems, such as virtual keyboards, smart wheelchairs, and smart home environments, must be pursued through close collaboration with end users. Such collaboration is essential to ensure a tangible functional impact on improving independence and quality of life [2, 31, 42, 52, 58].

4. CONCLUSION

This comprehensive review of 59 peer-reviewed studies, synthesized through a rigorous PRISMA-compliant framework, confirms a fundamental paradigm shift in the architecture of eye-controlled virtual keyboards: a transition from conventional threshold-based systems to sophisticated Artificial Intelligence (AI) frameworks. The analysis confirms that while EOG remains dominant due to its superior temporal resolution, the integration of deep learning architectures, such as CNNs, RNNs, and LSTMs, has established a new standard by consistently exceeding the 90% accuracy threshold. However, the operational efficacy of these systems is currently hindered by critical bottlenecks, including inter-user signal heterogeneity, environmental noise interference, and a significant lack of clinical validation within the target population of individuals with motor impairments.

As its primary contribution, this article posits that the next frontier for assistive technology lies beyond raw accuracy. Instead, it necessitates the development of adaptive AI models supported by transfer learning and the integration of ergonomic, portable hardware. These findings provide a strategic roadmap for future research to bridge the gap between experimental prototypes and robust, real-time assistive solutions for individuals with severe motor limitations.

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