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Electroencephalography Subject Detection: Opportunity or Threat?

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Abstract

Brain-computer interfaces (BCI) leverage neurophysiological features like electroencephalography (EEG) to enhance user-computer interaction. EEG's high temporal resolution and unobtrusiveness make it ideal for BCI systems, facilitating real-time interaction with minimal latency. Prior studies employed EEG across domains, including health and security. Researchers expanded EEG data within natural language processing and information retrieval (IR), facilitated by machine learning methods. While the primary intention of using EEG has been to enhance the search experience, the nature of EEG data collection may capture sensitive information about the subjects, such as their identities, beyond the intended use. This raises ethical and privacy concerns, which have yet to be addressed. This work explores the detection of participants' identities from their EEG. A case study was formulated, incorporating EEG data from 40 participants engaging in the single-session simultaneous capacity (SIMKAP) experiment. Each participant's EEG recordings were utilized to perform subject classification. Results show that deep learning models identify 40 individual subjects that can be revealed with an accuracy of up to 58.8% (SD 5%). Based on these findings, the benefits of EEG within IR, ethical dilemmas presented by its use, and potential solutions must be addressed before wider development and implementation of further EEG-IR systems.

Keywords

Ethics, Information Retrieval, Brain-Computer Interfaces, Subject Identification, EEG, Electroencephalography

1. Introduction

Electroencephalography (EEG) data has become one of the leading sources of subject physiological information that has seen significant success across a variety of domains, such as medical and security. As a result of this widespread adoption and success, works have begun to outline the domain's specific opportunities and threats posed by the use and reliance on EEG data [1–3]. For example, in works by [4], they demonstrate the ability to manipulate an EEG-based speller to output whatever the attacker desires with high success. In more recently, the use of EEG data has also been expanded to natural language processing (NLP) and information retrieval (IR) tasks, as within the domain of NLP, EEG has shown prominence in the decoding of semantic relationships and its applicability in direct EEG-to-Text decoding

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[4–6]. Similarly, in IR-related works, EEG data has been applied to assess the presence of information needs (IN) [7] and direct subjective relevance assessment [8], as well as these works, have begun to explore its viability to improve the overall search process using imagined queries [9]. However, the incorporation of EEG data into these domains could also introduce numerous unique ethical dilemmas that must be addressed in the context of its specific use cases for each of its downstream applications. The source of these ethical dilemmas is primarily a result inherently sensitive nature of EEG data as it captures the electrical activity of the brain, which can provide detailed insights into an individual's cognitive processes [10], emotional states [5], and potential health conditions [11]. Capturing and using this rich and intimate information for various applications and agendas poses several ethical challenges, including concerns about privacy, consent, data security, and the potential for misuse [12]. However, previous works have yet to outline the potential ethical concerns posed by the incorporation of EEG data into contemporary IR systems and potential solutions, more specifically, the use of EEG as a unique identifier for users that could be incorporated into future EEG-IR applications. As such, this work formulates three key research questions to facilitate our investigation:

RQ1: Is it possible to identify unique subjects from their EEG data?

RQ2: What are the potential threats posed by EEG subject detection within IR?

RQ3: What are potential solutions for ethical dilemmas of EEG subject detection within IR?

To explore each of these research questions, we propose a case study involving the use of EEG data from 40 subjects, provided by the STEW dataset [13], to train and evaluate four deep learning models gated recurrent unit (GRU), long short-term memory (LSTM), bi-directional gated recurrent unit (BGRU), and bi-directional long short-term memory (BLSTM), for subject identification. The results from this case study will inform the discussion of potential applications and ethical implications within the context of IR, offering guidance on how future IR systems incorporating EEG data should address these ethical concerns. The key contributions of this work are as follows:

- We demonstrate the feasibility of subject identification from EEG data collected during IR tasks, achieving an accuracy of up to 58.8% across 40 subjects using deep-learning approaches. This finding highlights significant privacy implications for EEG-IR systems.
- We provide a systematic analysis of how subject identification accuracy scales with participant numbers (10–40 subjects), revealing that even as the subject pool quadruples, classification accuracy remains well above random chance, suggesting persistent privacy concerns regardless of user base size.
- We present a comprehensive examination of the ethical implications specific to EEG-IR systems, including data protection, transparency, accountability, and fairness concerns, and propose potential solutions for addressing these challenges in future system implementations.

The remainder of this paper is organized as follows. Section 2 provides background information and related work, covering EEG fundamentals, the emergence of NeuraSearch, and existing ethical concerns in both EEG and IR domains. Section 3 details our methodology, including dataset preparation, preprocessing steps, feature extraction techniques, and the deep learning models employed in our study. Section 4 describes our experimental approach, including dataset preparation and cross-validation strategies. Section 5 presents our experimental results, demonstrating the feasibility of subject identification and analyzing how accuracy scales with participant numbers. Finally, Section 6 discusses our findings and their implications for EEG-IR systems, concluding with recommendations for addressing ethical challenges in future implementations.

2. Related Work

2.1 EEG

An EEG is a diagnostic procedure that captures the brain's electrical activity from the scalp. The recorded waveforms are presumed to reflect the activity of the brain's outer layer, the cerebral cortex, which is strongly associated with human thoughts, emotions, and behavior [14]. Recent advancements in

EEG-based brain-computer interfaces (BCIs) have expanded their applications across various domains [15, 16]. To monitor and record brain wave patterns, electrodes are affixed to predetermined scalp locations and linked to a computer. The placement of electrodes follows the International 10-20 System [8]. Signals are then transmitted to a computer for recording, where digital EEG systems convert EEG signal waveforms into numerical sequences. These sequences are updated based on the EEG recorder's sampling rate, indicating the frequency at which waveform data is sampled from each electrode. Sampling rates are typically measured in hertz (Hz); for example, 512 Hz corresponds to 512 samples per second [17]. One notable advantage of EEG is its capacity to observe millisecond-scale brain activity in real-time. However, EEG signals are susceptible to contamination by noise or artefacts, as identified by neuroscientists. Artefacts may stem from external or internal sources. Hence, artefact removal is a crucial preliminary step to enhance the signal-to-noise ratio of acquired EEG data [18]. The advantages of EEG data have made it unique among neurophysiological measures, leading to its widespread incorporation into modern BCI systems [19].

2.2 NeuraSearch

The increased adoption of EEG techniques across various disciplines, specifically IR, has led to the emergence of a novel field termed NeuraSearch [4, 5, 7, 8, 16]. This area sits at the intersection of IR and neuroscience, aiming to streamline IR processing by leveraging neurophysiological features [16, 19, 20]. For instance, a study conducted on 24 participants monitored their brain activity using a functional magnetic resonance imaging (fMRI) device during a question-and-answer (Q&A) session to pinpoint the physical brain activations associated with realizing an information need [20]. Similarly, another investigation recorded EEG data from 24 individuals during a Q&A session, aiming to track how information needs manifest in real time [7]. The results of this work revealed that information needs are present in the brain even before individuals become consciously aware of them. In a separate fMRI study with 18 participants tasked with evaluating image importance, distinct brain areas associated with determining the relevance of information objects were identified [21]. Likewise, an analysis of EEG data from 25 participants during a Q&A task revealed unique event-related potentials (ERPs) corresponding to varying relevance levels . These studies, focusing on the use of neurophysiological data within the IR field, align with the NeuraSearch framework, exemplifying its potential to enhance IR processes. By integrating EEG data within IR systems, NeuraSearch aims to create more intuitive and efficient search experiences [19]. This approach not only promises to improve the accuracy of detecting information needs and relevance assessments but also paves the way for real-time, user-centred IR applications. Recent studies have also explored the use of EEG data for emotion recognition and cognitive state assessment, which could further enhance personalized IR [22–24].

2.3 Ethical Concerns of EEG

Within the medical domain, the works highlight the physical safety risks of such systems regarding non-invasive EEG devices and how they may negatively affect the plasticity of the brain in developing children and adults. In another study by [25], the researchers stress that future EEG systems may cause users to become increasingly reliant on them, meaning that if the system were to fail, it may increase the likelihood of mistakes occurring, which, even in extreme situations, may put the user at risk of physical harm. Another concern surrounding the hardware of EEG devices is that it may give rise to the opportunity for malicious attacks and manipulation of EEG signals to occur. Another focus of past EEG-related ethics studies focuses on the security of the EEG data whilst in use. The major concern surrounding this is that EEG data may reveal sensitive information relating to the subject, such as their identity, brain-related health issues, mental diseases, and psychological traits [26]. Recent studies have further emphasized the potential of EEG data for biometric person identification, raising additional privacy concerns.

2.4 Ethical Concerns of EEG and IR

IR systems, such as search engines, conversational assistants, and recommender systems, are essential tools for sorting, selecting, and presenting relevant information to users [27]. With the advent of artificial intelligence (AI), these systems have become increasingly sophisticated, leveraging complex machine learning models to better understand and anticipate user needs [28]. The integration of EEG data into IR systems represents a development that could further add to the field by providing real-time, neurophysiological insights pertinent to IR. EEG data can offer unique advantages in understanding user intent and improving personalizing in IR systems. For instance, EEG-enhanced IR systems could utilize neurophysiological signals to detect user engagement [29–32], frustration [33], or satisfaction [34], thereby refining search results and recommendations dynamically. Additionally, EEG data could be employed for user identification and profiling [35], enabling systems to tailor interactions more precisely based on individual cognitive and emotional states. This integration has the potential to profoundly influence how users interact with information and make decisions, enhancing the overall user experience. However, the incorporation of EEG data into IR systems also raises significant ethical considerations that must be addressed [12, 14]. In recent years, the use of machine learning and neural models in IR systems has already brought numerous ethical challenges to the forefront, which are further complicated by the addition of EEG data. These ethical considerations include:

Transparency and explainability: Users should have a clear understanding of how EEG-enhanced IR systems operate and why certain results or recommendations are presented. This transparency is crucial for building trust and ensuring users are aware of the underlying mechanisms influencing their IR experiences [36].

Accountability and responsibility: Developers and maintainers of EEG-IR systems must be accountable for the impacts of their technology. They should ensure that their systems adhere to ethical standards and are designed with the potential consequences of their use in mind, including unintended effects on user behavior and decision-making [37, 38].

Fairness and bias: EEG-IR systems must be rigorously evaluated to mitigate biases that could arise from training data or the algorithms themselves. It is essential to prevent skewed results based on gender, race, ethnicity, religion, or other sensitive characteristics, thereby ensuring equitable and inclusive access to information [39–41].

Recent studies have also highlighted the need for ethical guidelines in the development and deployment of AI-enhanced marketing and IR systems, particularly concerning consumer privacy and data protection. As EEG data becomes more integrated into these systems, addressing these ethical concerns becomes increasingly critical.

3. Methodology

3.1 Dataset

For our case study, we utilized the Simultaneous Task EEG Workload (STEW) dataset [13] to discern subjects based on their EEG data. The STEW dataset is an open-source repository compiled through a single-session simultaneous capacity (SIMKAP) experiment, establishing a cognitive workload environment with multiple tasks. EEG data from 40 individuals were collected using a 14-electrode system and sampled at 128 Hz. Participants underwent two experimental scenarios: a resting condition and a testing condition. In the resting state, individuals sat in a chair without performing tasks for 3 minutes while their EEG data was recorded. During the testing conditions, subjects engaged in the SIMKAP activity, with EEG data recorded during the last 3 minutes, considered the workload condition. To mitigate transitional activity impact between tasks, the initial and final 15 seconds of each recording were excluded, resulting in a recording length of 150 seconds. Subsequently, participants rated their

perceived mental workload (MWL) on a 9-point scale, aiming to validate workload increment during the SIMKAP test compared to the resting condition. This EEG dataset offers a diverse subject range, enabling analysis of how the number of subjects exposed to deep learning models influences prediction accuracy. Moreover, the dataset encompasses EEG recordings from subjects tested across various experimental conditions, effectively showcasing EEG-based subject detection's reliability and efficiency in different scenarios.

3.2 Preprocessing

When recording EEG signals, external sources such as mobile devices and recording equipment, as well as internal electrical sources stemming from the subject's physical movements, can induce electrical interference, manifesting as noise and artefacts in the final EEG recording [42, 43]. To ensure EEG data is suitable for deep learning systems, it is important to mitigate this interference through the application of preprocessing methods [44]. Prior studies have demonstrated that noise and artefact removal positively impact classification performance [44]. Neuroscientists have traditionally utilized manual methods for EEG data preprocessing, entailing the identification and elimination of noise and artefacts within recorded EEG channels [45]. While effective, these methods are time-intensive and require expert intervention, posing challenges for processing large datasets. Moreover, manual procedures may introduce bias when human operators examine and remove artefacts [45]. In this investigation, we employ automated systems to speed up processing and mitigate potential human bias in the analyzed EEG data. For data preprocessing, we rely on the MNE-Python library [46]. Initially, a bandpass filter [47] was applied to the data, restricting it between 0.5–40 Hz. EEG signals within this frequency range exhibit a strong correlation with the brain's activation frequencies [48]. Consequently, signals outside this range are likely noise or artefacts stemming from electrical interference or muscular activity in the subjects.

3.3 Feature Extraction

Feature extraction can be applied to EEG data to enhance the predictive quality of machine learning models [32]. It achieves this by first reducing the dimensionality of the otherwise high-dimensional EEG data, thereby simplifying the data and retaining only the most relevant information [49]. This reduction not only decreases the computational load but also mitigates the risk of overfitting, leading to more robust and generalized models [50]. Furthermore, feature extraction techniques capture temporal dynamics and patterns in EEG signals, facilitating the effective modelling of temporal dependencies. In our study, we conducted feature extraction by computing a range of features from the frequency domain, temporal domain, non-linear domain, and linear domain. The features within each group are delineated below:

Frequency domain features: In this domain, four power spectral density (PSD) bands of delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–40 Hz) band were calculated [51, 52].

Statistical features: Mean, variance, skewness, and kurtosis [44, 53].

Morphological features: Curve length, the number of peaks, and average nonlinear energy [44, 53].

Time-frequency features: Wavelet transform [44].

Linear feature: Autoregressive coefficient (AR) with P = 2 [44].

Nonlinear feature: Approximate entropy (ApEn) and Hurst exponent (H) [53].

3.4 Models

Prior works have demonstrated the capabilities of modern machine learning models for EEG classification. In particular, recurrent neural networks (RNNs) [14] have seen substantial success given the temporal nature of EEG data, and specific uses in EEG subject identification [44, 53]. Hence, for this study, we implemented the following four RNN architectures: the GRU [54], LSTM [55], BGRU, and

BLSTM [56]. An overview of each implementation is detailed in Table 1. Each layer type is represented by an abbreviation: GRU, BGRU, LSTM, BLSTM, and Dense (denoted as G, BG, L, BL, and D, respectively). For instance, a model BL_{128}-L_{64}-L_{32}-D_{16}-D(n), a model consisting of a BLSTM layer with 128 units, an LSTM layer with 64 units, a Dense layer with 16 units, and an additional Dense layer with n units, corresponding to the number of subjects for classification. The models were trained with a learning rate of 0.0001 and the Adam optimizer, with a batch size of 32, and categorical cross entropy as the loss function. To ensure effective training of our deep learning models, we implemented early stopping to mitigate overfitting, with a maximum training epoch set at 200 and a patience equal to 5. Each of the model architectures was determined based on prior research and preliminary experiments.

Table 1. RNN models with architecture

	GRU	BGRU	LSTM	BLSTM
Layers/nodes	G_{128}-G_{64}-G_{40}-$D_3$2-D(n)	BG_{12}8-G_{64}-G_{32}-D_{16}-D(n)	L_{128}-L_{64}-L_{40}-D_{32}-D(n)	BL_{128}-L_{64}-L_{32}-D_{16}-D(n)

3.5 Metrics

Evaluating our models, we assessed their performance using accuracy and F1-score metrics [57] (see Equations 1 and 2). Specifically, for the classification task at hand, we defined true positive (TP) instances as those where the model correctly identified positive cases, while false negative (FN) instances were misclassifications of negative cases. Similarly, true negative (TN) instances were correctly identified as negative cases, whereas false positive (FP) instances were misclassifications of positive cases. This approach enabled precise measurement of each metric, considering the nuanced factors involved.

Accuracy is the sum of the number of true positives and true negatives divided by the total number of examples.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

F1 score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance:

$$F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (2)$$

where

$$\text{Precision} = TP / (TP + FP) \quad \text{Recall} = TP / (TP + FN).$$

4. Experimental Setup

4.1 Dataset Preparation

The dataset contains two text files, lo and hi, for each participant, which contain EEG data recordings from the 14-channel electrode cap affixed to their scalp during the SIMKAP experiment. The log files contain EEG data from the resting state when participants were asked to sit in a chair and perform no tasks, while the hi files contain EEG data from when they were actively participating in the SIMKAP test. To ensure that the data in each file was suitable for feature extraction, we applied the processing steps discussed in Section 3.2 to the lo and hi data. Subsequently, feature extraction was achieved by adopting a time window of 4 seconds to calculate each of the features detailed in Section 3.3. As the STEW dataset has a sample rate of 128 Hz, and the lo and hi experiments are 2.5 minutes long (or 150 seconds), this meant that after feature extraction, there were 19,200 sample points for each of the 14 channels (150 × 128). For each 1-second window, we extracted features using 128 rows of EEG data for each of the 14 channels, resulting in a total of 150 sample points for the feature sets. With 14 channels and 11 features to be extracted per channel, the feature set's width is 154. Therefore, the final feature files

have dimensions of 150 × 154. To construct the sequences necessary for the RNNs detailed in Section 3.4, we adopted a rolling window strategy with a window length = 4 samples. Each sample window had dimensions of 4 × 154, with 154 representing the 11 features extracted per the 14 channels. A total number of 37 windows were created for the lo and hi feature datasets per subject (150/4 = 37.6, rounded down = 37).

4.2 Time Series Cross-Validation

To ensure an accurate evaluation of each model's results, we employed time series cross-validation (TSCV) methods tailored for sequential data like EEG signals. Traditional cross-validation divides the dataset into K folds, training on K–1 folds and evaluating the remaining fold, but it's unreliable for sequential data. In our study, we utilized expanding window and blocked window TSCV strategies. In the expanding window approach, the training dataset grows sequentially in each fold while the test set maintains a constant size (20% of the entire dataset), ensuring the sequential nature of the data is respected. A 10% validation set is carved from the final portion of each training fold. On the other hand, a blocked window TSCV keeps the sizes of training, validation, and test sets constant across folds. It starts from the first data point and shifts the window for each fold, ensuring every sample within a window is utilized. Both strategies use 5-fold TSCV in our study, providing reliable results while mitigating overfitting.

4.3 Experiment Conditions

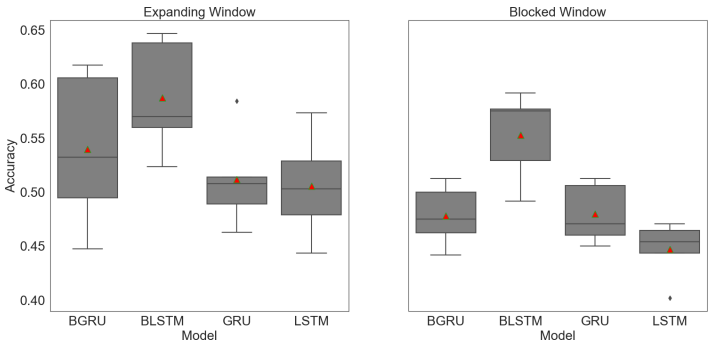
To address RQ1, we designed our first experiment condition, "Subject Classification," where we trained each of the RNN models described in Section 3.4 using the maximum number of available subject EEG datasets (40 subjects). The objective was for the models to classify individuals based solely on the provided EEG data. To address RQ2, our second experiment condition, "Varied Subject Classification," involved varying the number of subjects incrementally: 10, 20, 30, and 40. We repeated each of these experiment conditions using both expanding and blocking window TSCV strategies. To determine if the results were statistically significant relative to the baseline model results, a *t*-test was applied with a *p*-value = 0.05; all results presented in this study were found to be statistically significant.

5. Results

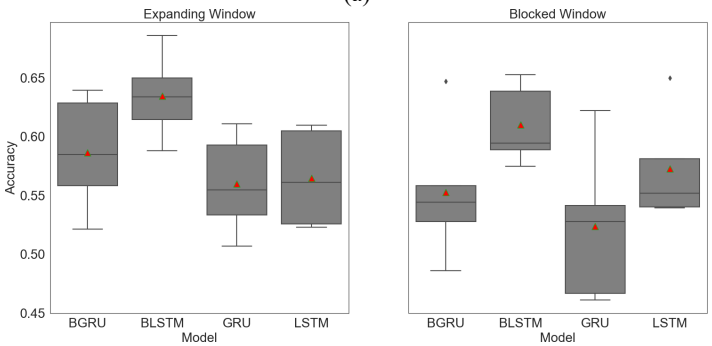
5.1 Subject Classification

The results presented in Fig. 1(a) illustrate the accuracy of each RNN variation when trained on a maximum of 40 subjects, using both TSCV strategies. The BLSTM model achieved the highest average accuracy among all models, scoring 58.8% (mean F1-score 57%, standard deviation [SD] 5.3%) with the expanding window strategy. This is 3.5% higher than the score of the BLSTM model trained with the blocked window strategy, which achieved an accuracy of 55.3% (mean F1-score 54%, SD 4.1%). This trend of expanding window TSCV strategy models outperforming their blocked window counterparts is consistent across other models. Specifically, the GRU, LSTM, and BGRU models showed improvements of 3.2%, 5.9%, and 6.2% in accuracy, respectively, over their blocked window counterparts. The average accuracy scores across both TSCV strategies were 49.6% for the GRU model, 47.65% for the LSTM model, and 50.9% for the BGRU model. Although the expanding window models achieved higher accuracy scores, the blocked window models exhibited a lower average variance of 2.4%, making them preferable when prediction consistency is crucial. These findings directly address RQ1, demonstrating that EEG data can be used to predict up to 40 unique subjects, with the highest accuracy being 58.8% (mean F1-score 57%, SD 5.3%) using the BLSTM model. While accuracy scores are reported in Fig. 1, F1-scores are provided here for key results to offer additional performance context. The implications of

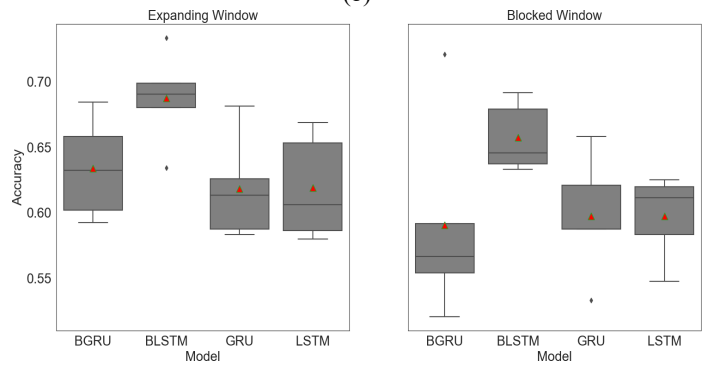
this subject identification capability and its potential threats (RQ2) as well as possible solutions (RQ3) are discussed in detail in Section 6.3.



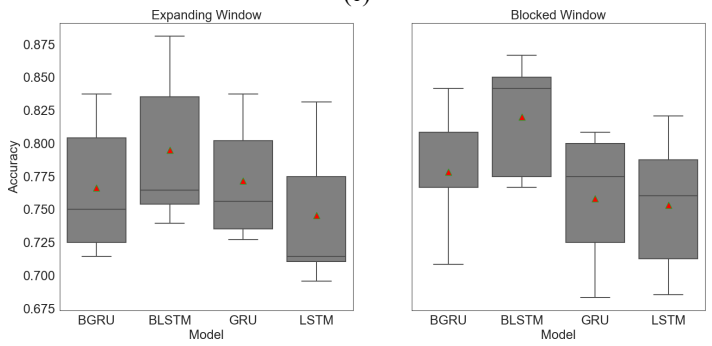
(a)



(b)



(c)



(d)

Fig. 1. Expanding and blocking TSCV model results on different subject counts: (a) 40 subjects, (b) 30 subjects, (c) 20 subjects, and (d) 10 subjects.

5.2 Varied Subject Classification

At a subject count of 30 in Fig. 1(b), expanding window models generally outperform their blocking window counterparts, except for the LSTM model, which scores 57.3% (mean F1-score 56%, SD 4.6%), 0.8% higher than its expanding window counterpart. The highest performing model is the BLSTM, with accuracies of 63.5% (mean F1-score 62%, SD 3.7%) for expanding and 61% (mean F1-score 60%, SD 3.4%) for blocking, showing a 4.7% increase from 40 subjects. In Fig. 1(c), the expanding window BLSTM model achieves the highest performance at 68.8% (mean F1-score 67%, SD 3.6%), 3% higher than the blocking window counterpart and 5.3% higher than at 30 subjects. Other expanding models (GRU, LSTM, and BGRU) outperform blocking models by an average of 2.86%, with scores of 60.75%, 60.8%, and 61.25%, respectively. Fig. 1(d) shows that blocking window models outperform expanding models. The highest performing model is the blocking window BLSTM, scoring 82% (mean F1-score 81%, SD 4.6%), 2.5% higher than its expanding window counterpart and 13.2% higher than at 30 subjects. Blocking models average 1.13% higher than expanding models, with GRU, LSTM, and BGRU scoring 76.5%, 74.9%, and 77.2%, respectively. Table 2 shows that as the number of subjects decreases, model accuracy increases. The differences in average scores between 10–20, 20–30, and 30–40 subjects are 14.71%, 5.04%, and 6.66%, respectively. While accuracy scores are reported in Fig. 1(a), F1-scores are provided here for key results to offer additional performance context.

Table 2. Average model score across both TSCV strategies

Subject count	Average model accuracy (%)	Average baseline accuracy (%)
40	50.92	2.5
30	57.58	3.3
20	62.62	5
10	77.33	10

6. Discussion & Conclusion

6.1 Case Study Results

This paper presents a case study on subject detection using EEG data to explore its benefits and ethical considerations in IR. Our findings show that subject detection is feasible with deep-learning models, with the BLSTM model performing best among the models tested (GRU, LSTM, BGRU, BLSTM). We investigated the effects of two TSCV strategies on subject detection accuracy across different subject counts. The expanding window strategy provided the best performance for 20, 30, and 40 subjects, while the blocking window strategy was more effective for 10 subjects. This suggests that blocking TSCV is optimal for tasks with 10 or fewer subjects, whereas expanding TSCV is preferable for more than 10 subjects. As expected, reducing the number of subjects increased model accuracy. Specifically, accuracy was 77.33% (mean F1-score 76%) with 10 subjects and only dropped by 26.41% when the subject count was quadrupled. This insight can guide future systems in narrowing down probable subjects, using techniques like beam search, to enhance performance. While we primarily report accuracy metrics throughout the paper, F1-scores are provided for key results to offer additional performance context.

6.2 Opportunities of EEG in IR

For many years, user profiling and monitoring have been key aspects of IR, supporting search engines, conversational agents, and recommender systems [27]. User profiling systems collect data to understand user needs, interests, behaviors, and preferences, enhancing the IR system's ability to meet users' information needs [27]. With advancements in NeuraSearch, EEG-integrated search platforms are likely

to emerge, offering new possibilities in IR [20, 58]. This study showcases the potential of EEG data as a powerful tool for user identification within IR systems. By utilizing EEG signals as unique identifiers, future IR platforms could track and analyze specific user interactions, linking them to individual EEG profiles. This integration holds the promise of both implicit and explicit penalization, allowing IR systems to deliver tailored results in real-time based on neurophysiological markers. One of the key advantages of EEG-integrated IR systems lies in their ability to gauge the relevance of information objects and the user's level of attention instantaneously. By monitoring neural activity, these systems can prioritize content based on cognitive engagement, ensuring that users receive the most pertinent information at any given moment. This real-time assessment of user attention and interest represents a significant leap forward in IR technology, offering unparalleled responsiveness and accuracy in content delivery. This integration of EEG data in IR systems presents a critical privacy paradox: while EEG signals can significantly enhance search personalization and user experience, our findings demonstrate that these same signals can reveal user identities with considerable accuracy. This capability becomes particularly concerning in IR applications where users might expect anonymity or where multiple users share the same device. The ability to identify users through their EEG patterns, even when the data is collected for other purposes like measuring search satisfaction or cognitive load, introduces substantial privacy risks that could undermine user trust and system adoption. This risk is especially significant for IR applications in sensitive domains such as healthcare IR or academic research, where user privacy expectations are typically high.

6.3 Threats and Potential Solutions in EEG-IR Systems

The integration of EEG data into IR systems opens up new possibilities with substantial advantages, yet simultaneously introduces crucial ethical considerations. In this section, we explore these ethical dilemmas and offer potential solutions for each.

6.3.1 Data protection in EEG-IR systems

EEG data is inherently sensitive, encompassing a wealth of user-specific information, including brain-related health conditions, mental health diagnoses, psychological attributes, and even individual identity markers, as evidenced by this study's findings. Any unauthorized access, theft, or loss of this data could result in significant harm and repercussions. Therefore, future IR systems must incorporate EEG data to implement robust security protocols to safeguard against potential breaches. Furthermore, transparency regarding data collection methods, associated risks, and usage purposes is essential, particularly in functions like subject profiling within IR systems. Compliance with regulations such as the General Data Protection Regulation (GDPR), which classifies EEG data as "sensitive data," is essential to ensure ethical and legal standards are upheld before these systems are deployed for public use.

6.3.2 Accountability and responsibility in EEG-IR systems

Accountability and responsibility are fundamental in ensuring the ethical development and deployment of EEG-IR systems [37, 59], emphasizing the need for developers to bear responsibility for system actions and impacts. Ethical ramifications related to EEG data usage, societal implications, and legal compliance underscore the importance of addressing accountability and responsibility in system design and implementation [37, 59]. To navigate these challenges, developers must prioritize ethical design practices, engage with stakeholders, implement transparency and accountability mechanisms, and establish processes for continuous monitoring and evaluation. For example, developers could incorporate user consent mechanisms, conduct regular ethical impact assessments, and establish user feedback mechanisms to uphold accountability and responsibility in EEG-IR system deployment [37, 59]. By implementing these measures, developers can mitigate ethical risks and ensure alignment with societal values and expectations in IR applications [37, 59].

6.3.3 Fairness and bias in EEG-IR systems

Fairness and bias are critical considerations in the development and deployment of EEG-IR systems, aiming to mitigate disparities and ensure equitable treatment of users [37, 59]. The integration of EEG data introduces potential biases stemming from various sources, including data collection methods, algorithmic biases, and societal biases. These biases can manifest in differential treatment, representation issues, and unfair outcomes, compromising the integrity and trustworthiness of EEG-IR systems [37, 59]. To address fairness and bias concerns, developers must adopt strategies to identify, mitigate, and prevent biases throughout the system lifecycle. This includes employing diverse and representative datasets, implementing bias detection and mitigation techniques, and conducting rigorous fairness evaluations [37, 59]. Additionally, stakeholders should prioritize inclusivity, diversity, and fairness in system design and decision-making processes, fostering a culture of fairness and equity in EEG-IR system development. By proactively addressing fairness and bias, developers can uphold ethical principles, promote inclusivity, and enhance the reliability and effectiveness of EEG-IR systems in serving diverse user populations [37, 59]. The above analysis of fairness and bias considerations completes our response to RQ2 and RQ3, demonstrating both the significant ethical challenges of EEG subject detection in IR systems and proposing concrete solutions to address these challenges. The implications of our findings extend beyond immediate privacy concerns, potentially shaping the future development trajectory of both BCI and IR systems. For researchers, this work highlights the need to incorporate privacy-preserving techniques from the earliest stages of system design, rather than treating privacy as an afterthought. Future EEG-IR research should explore techniques such as differential privacy, federated learning, and privacy-preserving feature extraction methods that could allow the benefits of EEG data without compromising user privacy. From a policy perspective, our findings suggest the need for specialized regulatory frameworks that address the unique challenges of neurophysiological data in IR applications. Current data protection regulations may need to be updated to specifically account for the sensitive nature of EEG data and its potential for unintended user identification. Additionally, the development of standardized privacy impact assessments for EEG-IR systems could help ensure consistent evaluation of privacy risks across different applications and contexts.

In conclusion, this study underscores the potential of EEG data within IR systems while also highlighting critical ethical considerations. EEG stands out among neurophysiological techniques due to its high temporal resolution, portability, and non-invasiveness, making it suitable for real-time user-computer interactions. Our case study demonstrated the capability of machine learning models, particularly deep learning architectures such as GRU, LSTM, BGRU, and BLSTM, to classify subjects based on EEG data with an accuracy of up to 58.8%. This finding suggests that EEG can provide valuable insights for IR applications, such as determining information needs, formulating queries, assessing cognitive load, and evaluating document relevance. Despite these promising results, our study has several limitations. First, the experiments were conducted using a single dataset (STEW) in a controlled laboratory environment, which may not fully represent the variability of real-world conditions where EEG-IR systems would be deployed. Second, our analysis focused on a limited set of deep learning architectures, potentially overlooking other approaches that might yield different accuracy-privacy trade-offs. Third, the study did not explore countermeasures such as differential privacy techniques that could mitigate identification risks while preserving utility. However, the collection and use of EEG data raises significant ethical concerns. EEG data can inadvertently capture sensitive information, including subject identities, necessitating stringent ethical standards and privacy protections. The study advocates transparency in the use of EEG-enhanced IR systems, ensuring users understand how their data is handled and safeguarded. Developers must be accountable for the ethical implications of their systems, striving to mitigate biases and ensure fairness. Future IR systems integrating EEG data must address these ethical dilemmas to leverage the benefits of EEG without compromising user privacy and security. This study highlights the importance of balancing technological advancement with ethical considerations in the

development of EEG-enhanced IR systems, emphasizing the need for ongoing vigilance as these technologies continue to evolve

Author's Contributions

Conceptualization, NM, YM; Investigation, NM; Methodology, NM; Project administration, YM; Resources, YM; Supervision, YM; Writing of the original draft, NM; Writing of the review and editing, NM, YM; Software, NM; Validation, NM; Formal analysis, NM; Data curation, NM; Visualization, NM; Funding acquisition, YM.

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Competing Interests

The authors declare that they have no competing interests.

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