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The Application of EEG in Web Search Research: A Systematic Review on Sample Size, Active Authors and Results

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Abstract

Introduction. Notwithstanding the growing interest in employing electroencephalography (EEG) for web search research, studies presently being conducted continue to grapple with significant issues, namely, small sample sizes, variability in methodology, and limited generalisability. This systematic review seeks to address these particular issues by describing how EEG has been used in this field of research, addressing sample sizes, active authors, methodologies, and limitations.

Method. This systematic review employs the PRISMA framework to analyse the application of EEG in web search studies, focusing on sample sizes, methodologies, and challenges faced by researchers. A comprehensive search was conducted across multiple academic databases to identify relevant studies.

Results. Findings indicate that typical sample sizes in EEG studies range from 10 to 24 participants, largely due to resource constraints. Researchers encounter challenges such as biological artefacts affecting data quality, the complexity of emotional and cognitive states, and limitations in generalisability due to small sample sizes. Additionally, issues related to equipment quality and methodological consistency further complicate EEG research in this domain.

Conclusions. The application of EEG in web search research holds significant potential for enhancing our understanding of user interactions with search engines. However, addressing the identified challenges is crucial for improving the robustness and applicability of findings. Future studies should focus on refining methodologies and exploring innovative approaches to overcome existing limitations in EEG research related to web searches.

Keywords: Electroencephalography (EEG); Web Search; Systematic Review; Information Behaviour

1. Introduction

In today's fast-paced world of information technology, the blending of neuroscience with web search is proving to be an exciting area that could greatly improve how users interact with search engines. One fascinating tool in this field is electroencephalography (EEG), which allows us to non-invasively record the electrical activity of the brain. This technique is becoming increasingly popular in cognitive science and human-computer interaction (HCI) (Zhu & Lv, 2023). EEG provides direct, real-time measurements of neural activity related to attention, workload, and emotional states during search tasks. This offers insights that go beyond traditional behavioural or physiological indicators. By capturing brain activity with high temporal resolution, EEG enables researchers to track moment-to-moment changes in user engagement and relevance assessments. These insights can be used to inform the design of

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adaptive search interfaces and more intuitive algorithms. This systematic review explores the application of EEG in web search research. It highlights the integration of neuroscience with information retrieval and addresses the critical gap between existing feedback channels (such as clicks, dwell time) and eye tracking, which often fail to capture the underlying cognitive processes that influence search decisions. EEG data can uncover implicit feedback signals, such as neural indicators of "aha" moments or cognitive overload, which traditional logging methods do not reveal. Understanding these hidden cognitive processes is essential for developing next-generation search systems that can effectively respond to user needs.

The story of EEG began in the early 1900s and has grown significantly, especially recently, thanks to technological advances. Initially, EEG was all about basic recordings, but today we have impressive systems that can give us real-time insights into how our minds work. Modern EEG devices are designed for greater comfort and portability, which opens up possibilities for conducting studies in more naturalistic environments, although many current experiments still take place under lab specifications (Niso et al., 2023). This development is especially important when we think about how we use the internet. As web search has evolved from simple keyword searches to more complex systems that understand context and natural language, there is a growing need to truly understand how users think and behave when they search online. EEG offers a valuable method for exploring the cognitive aspect of web search behaviour, which could completely change the way we design and improve search experiences. These insights could inform future interface designs and adaptive search systems aimed at making web searches more intuitive and effective, though such applications remain an area for extended research.

The application of EEG in web search research holds significant promise for several reasons. First and foremost, EEG can greatly enhance our understanding of user behaviour. By providing insights into the cognitive processes that underlie user interactions with search engines, researchers can develop more intuitive and efficient search interfaces. This deeper understanding paves the way for designing systems that align more closely with the way users think and search (Kaushik & Jones, 2021).

Another key benefit of EEG is its ability to conduct real-time cognitive state analysis. Since EEG captures brain activity as it happens, researchers can analyse users' cognitive states during different stages of the search process. The real-time data can potentially inform the development of adaptive search algorithms, enabling search engines to adjust based on users' immediate cognitive responses, thereby enhancing the search experience (Aviles et al., 2024).

Additionally, EEG technology can be instrumental in emotion recognition during web searches. By adapting EEG-based emotion recognition systems, researchers can assess users' emotional responses throughout their search experiences. This capability is crucial for enhancing user experience as it allows for the tailoring of search results to better meet users' emotional needs and preferences (Erat et al., 2024).

The integration of EEG with other technologies, such as eye-tracking and virtual reality, also opens up exciting new possibilities for comprehensive user experience research in web search contexts. Combining these technologies can provide a multi-faceted view of user interactions and preferences, leading to more effective research outcomes and improved technology implementations (Zhu & Lv, 2023).

Finally, insights gained from EEG studies could significantly advance search engine optimisation (SEO) strategies. By understanding how users think and feel while interacting with search engines, SEO professionals can develop more effective methods for improving website visibility and relevance. This synergy between cognitive research and SEO can lead to enhanced online experiences for users, making their searches more fruitful and satisfying (Mladenović et al., 2022).

In recent years, we've witnessed remarkable progress in the field of EEG technology and its various applications in cognitive science and HCI. One of the most exciting developments has been the advent of wireless EEG devices. These innovations have opened up new avenues for research, enabling studies to become more natural and relevant, particularly in the context of web search (Niso et al., 2023). Moreover, the merging of artificial intelligence with EEG-based brain-computer interface (BCI) is paving the way for a deeper understanding of EEG signals. This synergy has the potential to create more sophisticated and reactive search systems, ultimately benefiting users (Cao, 2020). In the realm of web search, there are some emerging interesting trends, including the use of conversational agents that interact with users in natural language, such as chatbots and voice assistants, and the adoption of semantic search which aims to understand the intent and contextual meaning behind users' queries instead of simple keyword matching. These advancements strive to enhance user experience and align with the capabilities of EEG technology seamlessly, helping us gain insights into user interactions with search engines and optimising them accordingly (Kaushik & Jones, 2021).

A significant challenge in web search lies in accurately understanding user intention (what they seek) and satisfaction (whether they achieve their goal). Traditional internet search engines primarily rely on implicit feedback (such as clicks and dwell time), which can often be noisy and uninformative in practice. To develop more adaptive, user-aware systems, it is essential to identify additional real-time cognitive and affective signals that reflect users' mental states during their search processes. Although various data points (e.g., eye gaze, heart rate, skin conductance) have been explored in the past, their effectiveness in understanding feedback related to search intent and satisfaction is limited compared to real-time neural data. EEG represents a relatively underexplored potential solution, as it offers insights into cognitive and emotional responses tied to attention, workload, and relevance processing—the very foundations of search intention and satisfaction.

This research aims to delve into EEG studies within the context of web searching, particularly examining the challenges that researchers encounter when selecting appropriate sample sizes. Recruiting a large group of participants for EEG studies can present significant financial and logistical hurdles, making it essential to identify the most frequently utilised sample sizes in this domain. The review will explore key gaps in the existing literature, including limited sample sizes, inconsistent methodologies, lack of ecological validity, and underexplored cognitive phases in web search processes. It will also summarise the methodologies employed in EEG studies related to web search. By analysing findings from a range of studies, this research aspires to shed light on the current state of the field and pinpoint critical areas for future exploration. Additionally, the review will highlight notable researchers in this field, helping to underscore their contributions and influence on the subject. Ultimately, this work seeks to enhance our understanding of the methodologies and challenges that accompany EEG-based research in web searching, providing valuable guidance for future studies that aim to tackle these issues.

2. Methodology

2.1 Overview

This research follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Moher et al., 2009) to provide a well-organised and clear method for systematically reviewing the use of EEG in web search studies. The approach involves defining the research questions, creating a search strategy, conducting literature screening, and gathering and analysing pertinent data.

This review employs a qualitative synthesis rather than a meta-analysis approach, due to the heterogeneity and variability of study types, EEG paradigms, and outcome measures across studies. While a meta-analysis quantitatively synthesises data from studies that have measured the same outcomes in similar ways, qualitative synthesis summarises findings and interprets results across differing methods to identify patterns, gaps, and themes.

2.2 Research questions

To align with the goals of this study mentioned in the introduction section, this research will pose the following research questions:

1. What research questions have been addressed in past EEG-based web search studies, and how do they shape the thematic direction of the field?
2. Who are the key researchers and teams in EEG-based web search studies, and what specific research questions have they addressed?
3. What methodologies have been employed to address the research questions in EEG-based web search studies?
4. What limitations and challenges, including sample size constraints, do researchers face in EEG-based web search studies?
5. What are the findings of research using EEG in web searches?
6. What are the future directions for EEG-based web search research emerging from current results regarding ecological validity in real-world settings?

2.3 Search strategy

A thorough search approach was carried out utilising the following academic databases: PubMed, IEEE Xplore, Scopus, Web of Science, Google Scholar, ACM Digital Library, SpringerLink, and ScienceDirect. These sources were chosen to ensure comprehensive coverage of literature in neuroscience, computer science, and information science. Boolean operators (AND, OR) and phrase search techniques (using quotation marks for exact match) were used to construct search queries. For example, queries such as *"electroencephalography" AND "web search" AND "user behaviour"* were applied to retrieve studies containing these exact phrases (Table 1). It is necessary to mention that all the articles were in English.

To improve the accuracy of the literature search, quotation marks were used around key phrases, allowing for the finding of exact phrases, which reduced the inclusion of unrelated studies. As a result, the need for manual screening was minimised, creating a focused set of resources that were directly relevant to the research questions. While skipping quotation marks could have broadened the search results, it would have also resulted in a lot of irrelevant information being included. To ensure that no important studies were missed, phrase-based searches without quotation marks were complemented with targeted keyword searches in the reference lists of selected articles and through the use of citation-tracking tools. This two-step strategy facilitated the achievement of both accuracy and thoroughness, enabling the construction of a high-quality dataset while also reducing the risk of overlooking key literature.

2.4 Inclusion and exclusion criteria

Research was considered for inclusion if it met the following criteria:

1. It dealt with EEG applications in the context of web searching or information retrieval.
2. It presented original experimental data supported by a well-defined methodology.
3. It provided details on sample size and the design of the experiment.

Also, studies were excluded if they:

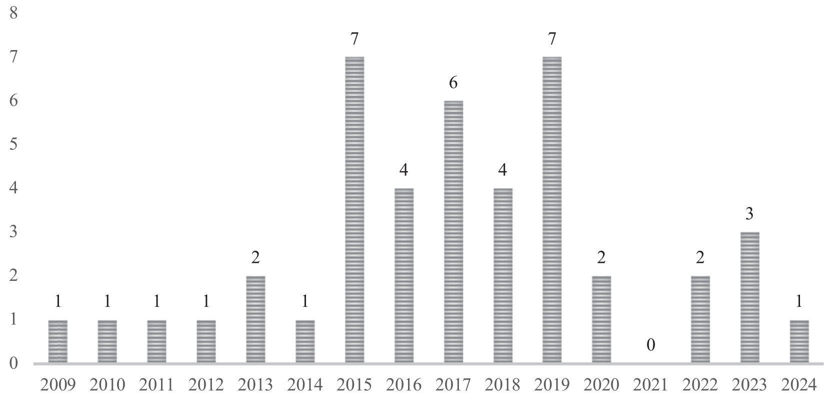
1. Did not include EEG data as a primary method (e.g., relied solely on eye-tracking, surveys, or interviews).
2. Focused on general cognitive or neuroscience tasks without a web search or information retrieval component.
3. Used inappropriate study designs (e.g., theoretical papers, editorials, or conceptual models without empirical data).
4. Review articles without original experimental results.
5. Were not peer-reviewed or were not published in English.

Figure 1 illustrates the number of research studies relative to EEG in the web search sphere each year. Although the total number of studies is small, the consistent emergence of research since 2009 in the field of neuroscience, HCI, and information retrieval demonstrates a burgeoning and interdisciplinary scholarly interest in this specialised area. The multidimensionality of studies and applications, reviewed in detail in this research, also indicates that it is time to synthesise and combine the literature in this area.

Table 1. Query Formulation Strategy for Finding the Articles Related to the Application of EEG in Web Search Research

"EEG"		"Web search"		"User behaviour"
OR	**AND**	**OR**	**AND**	**OR**
"Electroencephalography"		"Information retrieval"		"Relevance feedback"

Figure 1. Number of Studies in the Field of Application of EEG in Web Search Research



In the past 5 years, there have only been 8 studies that specifically explored the intersection of EEG and web search. While this limited number may seem discouraging, it actually underscores the necessity for a systematic review. The lack of extensive research in this emerging field emphasises the importance of synthesising the available evidence to pave the way for future investigations. By reviewing and critically analysing these valuable studies, several noteworthy trends have been identified, such as the increasing use of portable EEG devices and the rise of hybrid methodologies that combine EEG with other technologies.

2.5 EEG devices used across studies

The current review identified significant variability among the EEG devices utilised in the studies, particularly in terms of the number of electrodes, complexity, and intended applications. The initial studies examined (e.g., Xu et al., 2009) employed clinical-grade, multi-channel EEG systems, such as the Neuroscan NuAmps amplifier, which were suitable for laboratory environments. In contrast, later studies (e.g., Yehia et al., 2017) adopted portable or consumer-grade devices, such as the Emotiv EPOC, which are designed to be more user-friendly and applicable in real-time scenarios.

The devices examined can be categorised into 3 types:

1. High-density research systems (e.g., 32-64 channel BioSemi, Neuroscan, g.tec systems)
2. Mid-range EEG systems (e.g., 14-channel Emotiv EPOC, OpenBCI, MindWave)
3. Single-channel or wearable EEG headsets used in exploratory or hybrid BCI tasks

This diversity in EEG devices influences factors such as signal quality, setup time, portability, and the ecological validity of previous studies. High-density systems typically provide superior resolution in EEG signals, whereas portable devices offer greater ecological validity for real-world research.

2.6 Data extraction

Important details, including sample size, EEG methods, context of use, and key results, were gathered. Information on frequently utilised sample sizes, encountered challenges, and gaps identified in the field was also noted.

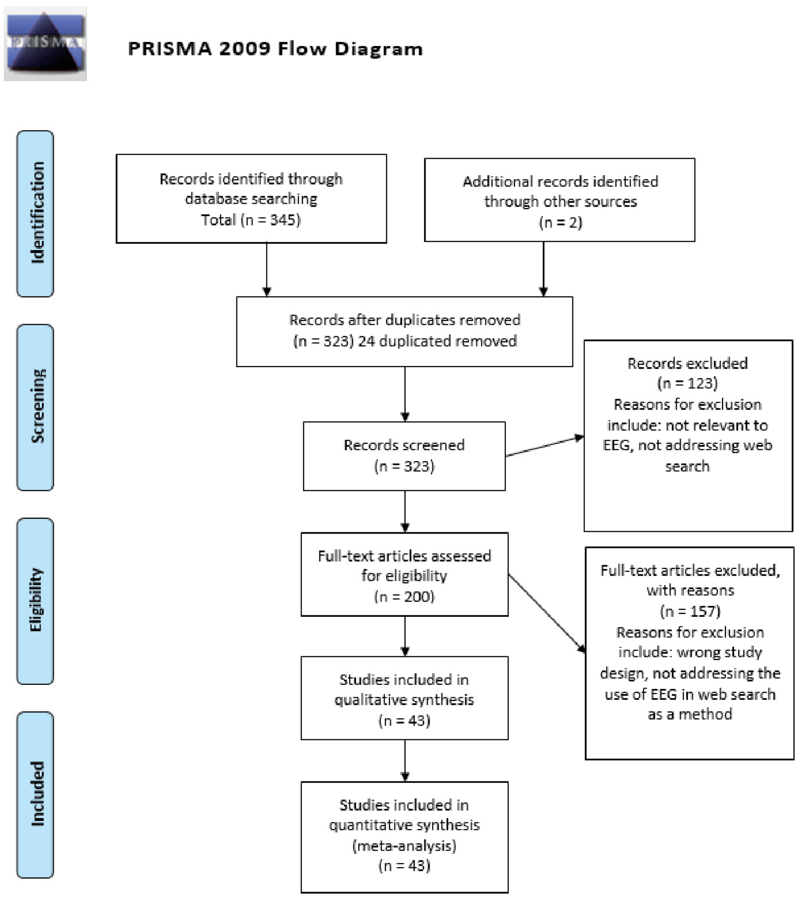
2.7 PRISMA flow diagram

A PRISMA flow diagram was utilised to illustrate the study selection process, keeping track of how many records were identified, screened, included, and excluded throughout the review (Moher et al., 2009). This approach provided transparency in recording the decisions made at various stages (Figure 2).

2.8 The research included in the systematic review

Appendix A presents the research included in this systematic review, detailing aspects such as sample size, methodology, findings, and overall insights into the application of EEG in the research.

Figure 2. PRISMA Flow Diagram for the Literature Review about the Application of EEG in Web Search Research



3. Results and Discussion

RQ1: What research questions have been addressed in past EEG-based web search studies, and how do they shape the thematic direction of the field?

EEG-based web search research has addressed several fundamental questions about utilising brain signals as direct input modalities. For example, Xu et al. (2009) used steady-state visual evoked potentials (SSVEPs) to facilitate cursor control as well as character input to Google searches, replacing standard means of input. Following that, Yehia et al. (2017) created an SSVEPs-driven interface with command detection accuracies over 86% and with well-defined navigation features during real-time browsing tasks. Simultaneously, an additional line of research using P300 paradigms, such as Martínez-Cagigal et al. (2017), demonstrated that people with multiple sclerosis could operate a web browser on their own using the oddball row-col paradigm, solidifying the potential of EEG as a hands-free input channel.

A second direction in this theme has focused on measuring cognitive load and engagement in the course of search tasks. Antonenko et al. (2010) utilised real-time EEG measures that can document small fluctuations in users' mental workload when operating hyperlinks as a dynamic measure of interface evaluation. Gwizdka and Cole (2011) also integrated EEG (alpha and theta power) with eye-tracking methods to identify high or low cognitive workload, claiming that adaptive systems could respond to user overload. Scharinger et al. (2016) demonstrated that lower power in the alpha-band corresponds with the recognition of search results that were relevant to an information need, suggesting neural correlates of what neural scientists often label the "aha" moment. Finally, Al-Samarraie et al. (2019) utilised EEG to directly assess layout designs for a search task, finding that single columns incurred less cognitive load than multi-column layouts.

Implicit relevance feedback has become a focus of research, in which EEG is used to measure any content users find relevant to what they are looking for, but they did not explicitly click on anything. Moshfeghi and Jose (2013) took EEG-derived affective signals and combined them with eye-tracking and behavioural data to increase relevance-feedback specificity, showing the multimodal benefits of EEG in contrast to univariate signals. Eugster et al. (2014) used multi-view EEG feature representations to classify term relevance, resulting in a 17% accuracy improvement over the benchmarking methods. Lastly, Golenia et al. (2018) demonstrated the decoding of ambiguous image search intents in 86% of trials using a combination of EEG and gaze, highlighting the unique capability of EEG to disambiguate user goals.

As mentioned, numerous studies have indicated that similar EEG signals, including heightened P300 amplitude and some suppression in the alpha band, correlate with users' relevance judgments while evaluating search results. These neural signals emerge during or before the process of making explicit judgments, suggesting that EEG could serve as a potential real-time marker for relevance processing. However, it does not straightforwardly demonstrate a strong capacity to predict relevance or relevance decisions.

Acknowledging the aforementioned limitations of utilising the EEG system as a standalone methodology, researchers have sought to implement homogeneous multimodal systems. For instance, Jimenez-Molina et al. (2018) combined EEG inputs with photoplethysmogram (PPG) and electrodermal activity (EDA) inputs, and demonstrated successful classification of 4 levels of mental workload with an improvement in classification accuracy through the combined use of multimodal inputs. He et al. (2017) focused on the combination of EEG modality and electrooculography (EOG) signals by studying imagined hand movements and eye blinks to assist mouse movement at specific locations within a web browser, which was advantageous for readers as it was a precise and quick way to integrate data while performing textual comprehension tasks on the web. Finally, Gwizdka (2018) showed that algorithms using both a single-channel EEG attention metric and pupil dilation measurements were effective in distinguishing relevant from irrelevant pages, suggesting more promising forms of sensor fusion that can offer an even richer combination of inputs and establish deeper relevance with respect to an observer's attention.

More contemporary research has examined cognitive and affective states that may influence information search processes more subtly. For example, Sarraf (2019) derived EEG signatures to map participants' experience across the stages of the Information Seeking Process (ISP) - namely formulation, exploration, and collection - and identified unique neural and emotional patterns at each stage. This has led to the exploration of an adaptive, stage-aware search system. Similarly, Michalkova et al. (2022) linked early event-related potentials (ERPs) to a Feeling-of-Knowing (FOK) experience, marking indicators of preconscious awareness with respect to reformulating queries. Pinkosova et al. (2023b) reported a previously unrecognised P100 ERP component during relevance assessment and suggested an association with attention and working memory. They highlighted the possibility of new neurophysiological indicators to personalise information search in real time. In another research, Torabi et al. (in press) reveal significant variations in selective attention during different stages of web searching. They found that the judgment phase is marked by the highest alpha wave activity, indicating increased cognitive processing, while the question formulation and result evaluation stages exhibit lower alpha wave activity, suggesting a reduced cognitive load. This indicates that users' experience changes in both internal and external selective attention. Specifically, during the judgment phase, users tend to focus less on external stimuli and more on internal cognitive processes when assessing the relevance of web pages.

Collectively, these research studies—covering modalities of input, cognitive load, implicit feedback, multimodal fusion, and deep cognitive-affective modelling—have begun to mark a thematic progress in the use of EEG for web search. The field has advanced from proving that EEG can work to developing a responsive, adaptive, user-centric experience that uses subtle neural and physiological responses, toward a truly intelligent brain-based search experience. Table 2 shows the thematic classification of these studies.

Table 2. Themes in EEG-based Web Search Research

Theme	Core question addressed	Studies
1. BCI Input Modalities & Interaction	Can EEG signals (e.g., SSVEP, P300, motor imagery) serve as direct control channels for web search interfaces?	He et al. (2017, 2020); Lin et al. (2019); Martínez-Cagigal et al. (2017); Xu et al. (2009); Yehia et al. (2017)
2. Cognitive Load & Engagement Measurement	How can EEG reveal real-time cognitive workload, attention, or engagement during search tasks?	Al-Samarraie et al. (2019); Antonenko et al. (2010); Gwizdka & Cole (2011); Jimenez-Molina et al. (2018); Nel et al. (2019); Scharinger et al. (2016)
3. Implicit Relevance Detection & Feedback	Can we infer which terms, words, or images users find relevant purely from EEG signals?	Eugster et al. (2014, 2016); Golenia et al. (2015, 2018); Jacucci et al. (2019); Mohedano et al. (2015); Moshfeghi & Jose (2013); Pinkosova et al. (2020, 2023a, 2023b); Porta Caubet (2015); Ye et al. (2023)
4. Multimodal Fusion & Hybrid Systems	Does combining EEG with eyetracking, EOG, PPG, or EDA improve control accuracy or feedback precision?	Frey et al. (2013); Gwizdka (2018); Gwizdka & Cole (2011); He et al. (2017); Jimenez-Molina et al. (2018); Slanzi et al. (2015); Wenzel et al. (2017)
5. Information-Seeking Process & Metacognition	What neural signatures mark different search stages (e.g., formulation, exploration, collection) or metacognitive experiences (e.g., FOK)?	Chen et al. (2022); Michalkova et al. (2022, 2024); Pinkosova et al. (2023a, 2023b); Sarraf (2019)
6. Accessibility & Special Populations	How can EEG-driven search interfaces support users with disabilities, and how do device form factors affect search performance?	Debue et al. (2018); Martínez-Cagigal et al. (2017)
7. Feasibility, Prototyping & Integration	What frameworks and system architectures enable real-time EEG integration into web applications for adaptive search experiences?	Antonenko et al. (2010); Bansal et al. (2015); Chen et al. (2022); Golenia et al. (2015)

RQ2: Who are the key researchers and teams in EEG-based web search studies, and what specific research questions have they addressed?

Yashar Moshfeghi is the most active author with 8 publications using EEG, typically in conjunction with other modalities, as implicit feedback for relevance in information retrieval. In his first article with Jose, he established that affective and physiological signals, including EEG, provide information about implicit relevance that improves the accuracy of implicit relevance feedback beyond behavioural features (Moshfeghi & Jose, 2013). Most recently, he collaborated with Pinkosova to explore the neural signature of Saracevic's relevance model with EEG and fMRI, and aimed to better understand the cognitive processes in search relevance assessment by examining distinct time intervals of implicit judgements (Pinkosova & Moshfeghi, 2019).

Giulio Jacucci has produced 4 studies exploring relevance prediction in online and user-specific contexts. In Jacucci et al. (2019), the authors developed classifiers to predict the relevance of keywords in real-time from EEG and eye movement data, and achieve Area Under the Receiver Operating Characteristic Curve (AUROC) values that are significantly above chance for the majority of participants. This work directly tackles the scientific question of utilising implicit neural and ocular signals to model users' search intent without any kind of explicit feedback.

Zuzana Pinkosova's series of 4 publications provides a detailed study of relevance judgments and metacognitive effects. For example, Pinkosova et al. (2020) found that ERPs differentiated consistently and systematically between the graded levels of relevance in a question-answering study, appearing to link attentional allocation and semantic mismatch to specific ERP components. In subsequent research, Pinkosova identified the first described P100 component associated with attention and working memory while engaging in binary relevance judgments, as well as how self-perceived knowledge (SPK) modulates neural processing associated with the evaluation of relevance (Pinkosova et al., 2023a, 2023b).

Jacek Gwizdka published 3 important articles examining cognitive load and attention in web search. Gwizdka & Cole (2011) used EEG (alpha and theta power) and eye-tracking to distinguish between high and low cognitive load states while retrieving information. In Gwizdka (2018), he then showed that single-channel EEG attention indices, along with pupil dilation, differentiate relevant from irrelevant web pages. His work examines the question of how real-time physiological signals can be used to inform adaptive interfaces that respond to users' cognitive states (see Figure 3).

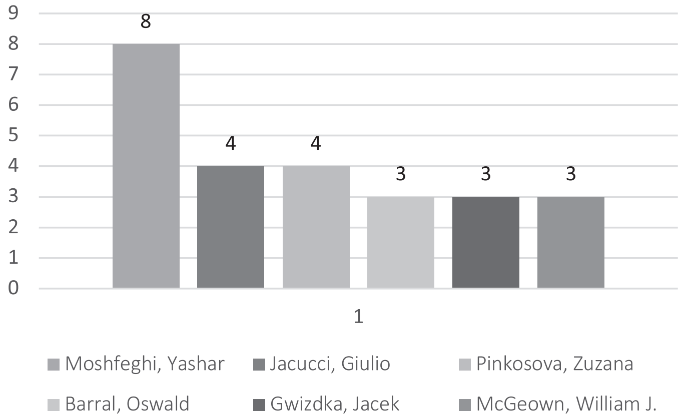
RQ3: What methodologies have been employed to address the research questions in EEG-based web search studies?

For the RQ3 study, the methodological approaches are specified by the 7 thematic areas coded into RQ1.

1. BCI Input Modalities & Interaction

In this thematic area, most prior studies adopted the classical paradigm in EEG so that individuals could indeed control an application without the use of their hands. Xu et al. (2009) created their command selection codes while using SSVEP stimuli, and harnessed a power spectral density (PSD) threshold algorithm to detect users' focus on a stimulus with flickering targets to indicate movement of a cursor and input

Figure 3. Researchers with the Most Number of Works in the Field of Application of EEG in Web Search Research



of characters on a computer screen. Yehia et al. (2017) similarly reproduced command selection studies without generating builds, but using an EEG device (Emotiv EPOC headset) and piloting SSVEP commands while reaching an over 86% detection rate. Moreover, the P300 "oddball" paradigm has been studied in this identified area. Martínez-Cagigal et al. (2017) used a row-column P300 speller to elicit P300 potentials, allowing individuals with multiple sclerosis to complete browsing tasks independently. In a recent study, Lin et al. (2019) merged SSVEP and eye-tracking while using Web Socket APIs, enabling another demonstration of hybrid speller and navigation BCIs.

2. Cognitive Load and Engagement Measurement

In this section, cognitive load is measured in the form of frequency-band power or ERPs, which are psychophysiological indications of mental workload. Antonenko et al. (2010) designed a custom Java-based framework for recording EEG in real-time for calculating cognitive load as users clicked hyperlinks. Gwizdka & Cole (2011) used an EEG method to extract alpha and theta band power to show significant correlations with eye-tracking measures, identifying high versus low workload states during search tasks. Scharinger et al. (2016) engaged in fixation-related EEG frequency analysis to show decreased parietal alpha power when participants recognised information relevant to the task. Finally, a multisensory approach (e.g., Jimenez-Molina et al., 2018) combining EEG with PPG and EDA signals provides a means to classify 4 discrete levels of cognitive workload for tasks using machine-learning models.

3. Implicit Relevance Detection and Feedback

Research methodologies in this section highlight techniques in the areas of feature extraction and classification. Moshfeghi & Jose (2013) developed affective (EEG) features as well as behavioural features, employing supervised classifiers as a means of yielding better implicit relevance feedback. Eugster et al. (2014, 2016) represented the EEG signals in multi-view feature spaces and trained high-precision classifiers, yielding up to 17% accuracy when predicting term-relevance. Rapid serial visual presentation (RSVP) paradigm (Mohedano et al., 2015), in which visual images are shown in rapid succession while ERPs are recorded, allows for detecting relevant items without explicit clicks (i.e., relevance ratings, using explicit relevance feedback). More recent research by Pinkosova et al. (2020, 2023b) examined graded ERPs and P100 components as a means of mapping neural responses at fine levels of relevance.

4. Multimodal Fusion & Hybrid Systems

These studies focus on the multimodal fusion of EEG with other data collection sensors. Frey et al. (2013) integrated eye-tracking and eye fixation-related potentials (EFRPs) in order to assess goal-relevant text. Slanzi et al. (2015) combined gaze data with gamma-band root mean square (RMS) and EEG variance data to find salient and relevant objects on a page. Wenzel et al. (2017) employed a system to classify (in real-time) task-relevant words by fusing both the EEG streams and eye-tracking streams. He et al. (2017, 2020) integrated EEG and EOG. Another study by Jimenez-Molina et al. (2018) included EEG fusion with 2 additional biophysiological measures: PPG and EDA, for a thorough workload assessment.

5. The Information-Seeking Process & Metacognition

Researchers have utilised ERP analyses and mixed methods to elucidate cognitive phases. For example, Sarraf (2019) recorded EEG data with psychophysiological data across stages of the ISP, namely query formulation, exploration and collection, and found neural and emotional signatures in the data across each of the phases. Michalkova et al. (2022) were able to identify early awareness prior to being consciously aware of a deficit of knowledge using ERP components. Similarly, Chen et al. (2022) decoded electrical signals in the brain to infer the level of satisfaction experienced by the user about the information provided and outside of the study systems or the platform, and reranked search queries by using APIs along with the metacognitive feedback process.

6. Accessibility and Special Populations

The methodological focus here is on clinical and comparative research studies. Martínez-Cagigal et al. (2017) adapted the P300 BCI paradigm for people with multiple sclerosis to assess improvements in levels of independence. Debue et al. (2018) conducted a within-subject comparison study between a laptop and touch-screen PCs, assessing task-level times, accuracy, and subjective satisfaction to inform an accessible interface experience.

7. Feasibility, Prototyping & Integration

This research is situated within the problem of system architecture and field deployments. Bansal et al. (2015) used EEG sensors that were embedded into a web browser code to track varying levels of attention and correlate with subjects' page scrolling. Antonenko et al. (2010) developed a semantic Java framework for real-time EEG capture in a web-based context. Golenia et al. (2015) demonstrated a live demo leveraging EEG and eye-tracking to differentiate between a series of image searches in a web app. Chen et al. (2022) combined an EEG decoding system with Sogou's query suggestion API to rerank search results based on implicit user satisfaction.

Spanning these themes, there is a methodological breadth extending from classic EEG paradigms to frequency and ERP-based analyses, machine learning classifiers, and now increasingly advanced multimodal fusions, establishing a strong technical pathway to the development of EEG-based web search engines.

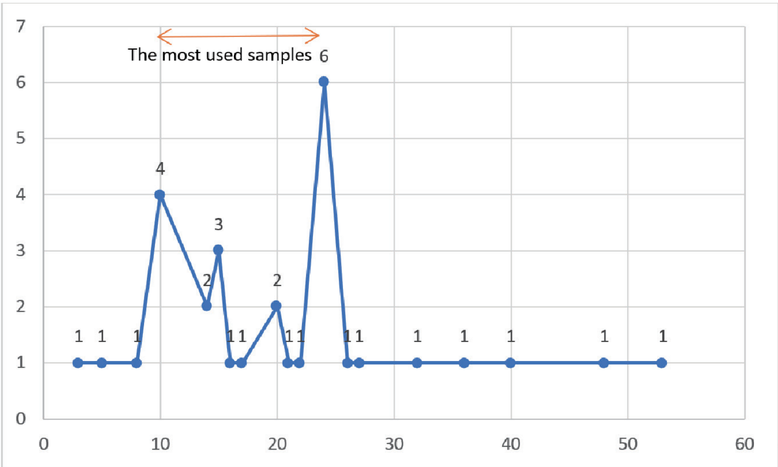
RQ4: What limitations and challenges, including sample size constraints, do researchers face in EEG-based web search studies?

Regarding EEG-based web search studies, small sample sizes are common due to the costs and logistical challenges associated with EEG technology. A review of 43 studies reveals that many of them (49%) had 10 and 24 participants, including studies with 20 participants (Allegretti et al., 2015), 24 participants (Michalkova et al., 2024; Pinkosova et al., 2023a), and just 10 participants (Xu et al., 2009). While the size of the sample supports a simpler data collection and a richer within-subject examination, it necessarily decreases statistical power and generalizability because the small sample may not represent the variability found in the larger user population (see Figure 4). The majority of the participants were university students or graduate research participants. A small number of studies included more distinct user groups, such as general internet users or subsets per profession (e.g., librarians, computer science practitioners). Yet overall, recruiting student groups was commonplace.

Apart from sample size, a well-known limitation to EEG data is that they are vulnerable to biological and environmental noise, including eye blinks, muscle actions, and electrical noise from sufficiently close electronics, that might mask the neural signals. Researchers addressed these limitations by utilising more advanced preprocessing and feature-extraction pipelines. For example, Eugster et al. (2014, 2016) developed multi-view EEG representations with high-accuracy classifiers to cleanly extract brain activity associated with relevance, while Pinkosova et al. (2020) used ERP analysis to examine graded levels of relevance, which was yet another example of advanced signal-processing methods.

The varying and dynamic nature of cognitive and affective states during web search makes things even more complicated.

Figure 4. Number of Samples in the Field of Application of EEG in Web Search



Moshfeghi & Jose (2013) showed that affective (EEG) and behavioural features can improve implicit relevance feedback when they occur simultaneously. However, studying the quick shifts in user intent during web searches is best accomplished through meticulous experiment planning and real-time analysis techniques. In addition, Golenia et al. (2015) used EEG and eye-tracking technology to disambiguate image search results, while recognising and sharing individual differences in neural response that provide challenges to a one-size-fits-all model.

Variable inter- and intra-subject characteristics must be considered when developing models utilising feature extraction and machine-learning algorithms. For example, Eugster et al. (2016) were able to predict relevance better by training a classifier using structured EEG features. Owing to individual differences, training generalizability appears to be limited without calibration involving several hours of subject-specific input data. This suggests that either a larger and more diverse dataset of participant data must be obtained, or an adaptive algorithm must be explored which is specifically capable of allowing learning on the limited data from the subject directly.

Limitations in equipment have also been major challenges. Research-grade EEG systems that offer high-density data are expensive, unwieldy, and deploying EEG systems is challenging outside of a laboratory setting. Some affordable or wireless headsets, such as the Emotiv EPOC used by Yehia et al. (2017), are beneficial because they are portable, but they compromise the signal quality of the data. There is a challenge to provide good data quality, easy usability, and affordability.

Inconsistency in methodology across studies, such as paradigms (e.g., SSVEP, P300, motor imagery), preprocessing steps, and the types of machine learning classifiers, makes it difficult to compare studies and/or conduct meta-analysis. For example, Xu et al. (2009) used a SSVEP-based PSD threshold approach, and Martínez-Cagigal et al. (2017) used a P300 oddball paradigm to study patients. The development of standardised protocols would improve reproducibility and promote the development of cumulative knowledge.

Lastly, logistical constraints—set up and calibration time, participant fatigue, and comfort level—may compromise the quality of the data collected. Debue et al. (2018) have documented that the ergonomics of the device and the length of the session impacted user experience and performance, and thus indicated that thoughtful session design and user comfort metrics are fundamentally important in order to collect reliable EEG data. Therefore, before significant advancement of EEG-based web search research can be realised, it is important to address the aforementioned shortcomings that have emerged in totality through more extensive, standardised and multimodal studies.

RQ5: What are the findings of research using EEG in web searches?

Research on values of EEG-based web search indicates robust evidence across the 7 thematic areas identified in RQ1, showing EEG has the potential for revealing user behaviour and improving search systems.

1. BCI Input Modalities & Interaction

The SSVEP paradigm is an extremely effective input modality. Xu et al. (2009) demonstrated character input and cursor control as an input for their Google search application, showing the promise of a brain-actuated web interaction by assessing only SSVEP. Yehia et al. (2017) achieved an average command detection accuracy of 86% based on command detection using an Emotiv EPOC headset with SSVEP stimuli. P300 oddball paradigm extends accessibility, as Martínez-Cagigal et al. (2017) showed a patient with a diagnosis of multiple sclerosis could autonomously navigate a web browser by using user navigation following P300-evoked potentials to sequence browsing behaviour. More recently, hybrid systems based on combining multiple modalities, such as the study of Lin et al. (2019), validated that 88.5% of spelling based on command detection could be achieved using a multimodal BCI interface that included SSVEP detection, fixation tracking and head pose all while using WebSocket APIs for a web interaction task.

2. Measurement of Cognitive Load and Engagement

The frequencies in EEG bands and ERPs are reliable indicators of workload. Antonenko et al. (2010) monitored the real-time cognitive load for users as they selected hyperlinks, and Gwizdka & Cole (2011) provided evidence of the alpha and theta power indexes of workload—high workload produced higher theta and lower alpha power during retrieval tasks. Scharinger et al. (2016) found decreased parietal alpha power associated with the recognition of relevant search results. Jimenez-Molina et al. (2018) accurately classified 4 discrete workload levels by using multisensor fusion of EEG, PPG, and EDA. Frey et al. (2013) combined EEG readings with eye-tracking data, showing improved cognitive processing during fixations related to goals, which bolstered findings about attention. Similarly, Moshfeghi & Jose (2013) illustrated that merging emotional, physiological, and behavioural signals could increase the precision of relevance feedback in search systems.

3. Implicit Relevance Detection and Feedback

Implicit feedback systems have increased engagement. Eugster et al. (2014) improved term-relevance prediction accuracy by 17% using multi-view EEG features and classifiers. Allegretti et al. (2015) found robust EEG differences between relevant and irrelevant pictures that would yield more accurate systems if feedback could be incorporated. Mohedano et al. (2015) enhanced EEG-based image relevance detection using an RSVP-based paradigm that outperformed mouse-based feedback. Pinkosova et al. (2020, 2023b) mapped graded ERPs, revealing a novel P100 component related to attention and working memory while assessing relevance.

Real-time feedback and system adaptation are further areas where EEG has shown promise. Wenzel et al. (2017) established that EEG could decipher the subjective relevance of words in real-time, allowing search systems to adjust dynamically to users' interests. More recently, Ye et al. (2023) demonstrated that incorporating brain signals into relevance feedback frameworks considerably enhances performance, particularly in challenging search scenarios. Lastly, the research has delved into emotional and behavioural metrics. Nel et al. (2019) underscored the effect that search engines and terms can have on users' emotional states, showing that EEG can measure feelings such as engagement and frustration during searches.

4. Combined Modality Fusion & Hybrid Systems

The combination of EEG with other signals improves performance. For example, Frey et al. (2013) investigated fixation-related potential in EEG (frpEEG) in time-synchronisation with eye-tracking to elicit recordings of goal-relevant text. Moshfeghi & Jose (2013) combined emotional EEG features with behavioural data to convey emotional homogeneity, improving the precision of relevance feedback. Wenzel et al. (2017) proposed real-time decoding of subjective word relevance through EEG and eye-tracking stream combination. Jimenez-Molina et al. (2018) attested that PPG and EDA improve EEG mental-workload classification.

5. Information-Seeking Process and Metacognition

EEG identifies distinct neural markers during different stages of the search process. Sarraf (2019) reported that there is greater attentional processing upon the initial stage of the ISP when the user formulates their query, and task satisfaction, at the final stage, during the collection of information, and specifically mapped cognitive and emotional processes to each of these ISP stages. Michalkova et al. (2022) concluded that early topographic ERP components indicated preconscious awareness of knowledge gaps, as the stages of the ISP unfolded. Lastly, Chen et al. (2022) successfully decoded brain signals to facilitate real-time user satisfaction feedback during information-seeking, which the researchers were able to use for dynamic query reranking through the Sogou API.

Furthermore, insights into browsing behaviour and preferences have been gleaned from EEG data. Bansal et al. (2015) linked user attention levels to specific web page sections, providing valuable knowledge for web design and ad placements. Katona et al. (2017) discovered that mid-gamma brainwave strength was notably higher during video browsing as opposed to static content, indicating differing cognitive demands. Finally, in terms of accessibility, Lin et al. (2019) developed a hybrid BCI web browser that utilises both EEG and eye-tracking data, achieving an impressive average accuracy of 88.5%. The innovation enables users with motor impairments to interact with web interfaces more effectively.

6. Accessibility and Special Populations

BCI-based systems provide assistive devices for users with limitations. Martínez-Cagigal et al. (2017) provided evidence that users with multiple sclerosis were able to perform web-based tasks using a P300 web browser with significantly increased autonomy. Debue et al. (2018) compared laptops with touch-screens and provided evidence for preferred devices in relation to various search tasks, while offering insight for the design of accessible interfaces.

7. Feasibility, Prototyping and Integration

Prototype systems provide evidence of real-world feasibility. For example, Bansal et al. (2015) embedded EEG sensors in a web browser to obtain a distinctive mapping of user attention to webpage sections, providing a platform for web design or advertisement practices. Antonenko et al. (2010) developed a Java framework that provided specific live analysis of EEG events in a web context. Golenia et al. (2015) provided a live demonstration combining both EEG and eye-tracking methods to provide specificity to disambiguated image search tasks. These prototypes led to further exploration of the feasibility of EEG-driven search interfaces and the adaptability of scaled types of EEG.

RQ6: What are the future directions for EEG-based web search research emerging from current results regarding ecological validity in real-world settings?

Future directions for EEG-based web search research increasingly emphasise boosting ecological validity by going beyond laboratory settings and filling existing methodological and practical gaps. EEG has demonstrated its utility in revealing cognitive states such as attention, relevance detection, and workload, but the vast majority of studies to date involve a static, tightly controlled environment, which may not reflect the complexities of the web search experience in daily life. As a consequence, the results may not generalise well to the real-world context, where users are consuming information in their online environment with fluctuating emotional states, distraction from the environment, and a varying number of devices.

A key future direction is the development of mobile EEG technology to facilitate the collection of research data in more naturalistic contexts (or an ecologically valid way). Recent research has begun to utilise portable and wireless systems, such as those of Yehia et al. (2017) and Katona et al. (2017)—but the deployment of these systems remains limited. Devices are the first steps to embarking on studies performed in the home browsing context, searching on the move with a smartphone, or in a multitasking format, where researchers can initiate surveying without removing the system, thereby better reflecting cognitive fluctuations and shifts in attention. Increasing mobile EEG research will significantly enhance the ecological validity of garments. Such improvement will allow us to better account for everyday distractions, emotional volatility, and the varying demands of tasks in real-life situations, rather than relying on highly controlled desktop computer studies.

A further avenue of inquiry is the inclusion of EEG along with rich behavioural data to create a more comprehensive understanding of web search behaviour. Many studies have collected eye tracking and mouse activity along with EEG signals, although many other studies still do not combine EEG signals with data collected simultaneously. Investigation of real-world behaviour would be enhanced through EEG by absorbing log data such as clickstreams, scroll behaviour, keystroke behaviour, and even voice inputs. This would be an additional form of multimodal fusion, which would establish strong cognitive modelling as well as integrate and improve the design of adaptive search interfaces responsive to overt and covert user cues.

Dealing with variance due to methodological inconsistency is also central to improving the external validity and generalizability of findings across contexts. The methodological inconsistencies currently observed in the web searching literature, ranging from differences in the number or configurations of electrodes used to measurement and preprocessing methods, result in massive challenges for comparing results or building upon any existing body of work. In this regard, studies should attempt to establish a standard methodology for the collection and analysis of EEG data in web search contexts. Defining shared baselines on a methodological level will be critical to moving forward, especially as studies have turned to obtain real-world studies with much variance in data methods.

The exploration of machine learning, particularly deep learning and transfer learning approaches, has emerged as an area of increasing interest in the feature extraction and analysis domain in order to model complex cognitive processes in real time. Current research still largely utilises traditional ERP and frequency-domain features, although dynamic web search behaviour creates highly non-linear and context-sensitive brain responses. If models were developed in deep learning, trained on mobile EEG data, and informed by behavioural context, we could enhance the robustness and applicability of EEG-based search adaptation systems.

A further gap in research pertains to inclusive research in specific contexts of users with cognitive or motor impairments. Very few studies (e.g., Martínez-Cagigal et al., 2017) have shown how BCIs can enable user engagement with disabilities. Far more research is necessary to understand how neurodivergent users generate cognitive responses to search tasks and how their cognitive behaviours could be incorporated into adaptive interfaces. Researching diverse cognitive profiles in research settings, and for search tasks that simulate real-world challenges—multitasking, emotional distraction, or information overload—would broaden the applicability of the findings from EEG-based studies.

Ultimately, ongoing research should explicitly model the complete search process, which encompasses the cognitive phenomenon of seeking, the building of queries, exploration, assessing relevance, and making decisions under uncertainty. Although some studies (e.g., Sarraf, 2019) have begun to map EEG responses on these individual phases of the full cognitive search process, it would be beneficial to model search in a more segmented fashion to provide insights. This would allow direct measurement of cognitive effort, feelings and SPK that all may fluctuate over time. The research will be informative in the design of interfaces that account for the complexity of not only user profiles but also user state to create more robust and usable web searches.

To summarise, if we truly want to expand ecological validity in future research using EEG and web search, we must move beyond static and individualised web-use, then towards mobile, adaptive, and inclusive research based in ecologically valid research to capture diversity of not only users' behaviours but interactions with context, spaces and thoughts.

4. Conclusion

This systematic review highlights the emerging role of EEG as a transformative tool in web search research. By meticulously examining existing methodologies, sample sizes, and challenges within the current literature, the paper emphasises how EEG can deepen our understanding of cognitive and emotional processes involved in web searches.

EEG has proven to be valuable in revealing the complex connections between cognition and emotion, allowing researchers to gain insights into user states like attention levels, cognitive workload, and emotional engagement as they navigate online. For instance, various studies have shown that EEG can effectively predict users' relevance judgments and measure their cognitive load. These insights have the potential to dynamically enhance search algorithms, leading to more personalised and responsive user experiences (Moshfeghi & Jose, 2013; Nel et al., 2019; Sarraf, 2019).

The review does, however, highlight persistent challenges associated with EEG research, including issues related to artefact management and the limited generalisability of findings due to small sample size. To overcome these hurdles, there is a need for methodological advancements, involving the development of standardised protocols, sophisticated artefact removal techniques, and the combination of EEG with other tools like eye tracking and behavioural metrics. Such innovations could strengthen the ecological validity of the findings and make them more applicable in real-world web search contexts (González-Ibáñez et al., 2016; Rashid et al., 2020; Zhang et al., 2024).

In EEG-based web search studies, a typical sample size of 10 to 24 participants is frequently utilised, as shown by various studies in this review. This range strikes a balance between the practical difficulties of conducting EEG experiments and the necessity for reliable data. While a smaller sample size is more cost-effective and easier to manage, it allows for controlled settings and in-depth analyses of individual subjects. However, this can restrict the applicability of the results to larger populations. Increasing sample size beyond this range requires considerable funding and careful planning, as EEG research demands significant resources due to the expenses associated with equipment, participant recruitment, and data analysis.

Moreover, the integration of EEG with other modalities, such as virtual reality and artificial intelligence, presents a significant opportunity for future research. By employing multimodal approaches, researchers can gather richer datasets that capture user behaviour more effectively, thereby enabling the creation of comprehensive user models and adaptive systems. This is particularly promising for applications requiring high accessibility, such as interfaces that serve individuals with physical or cognitive impairments (Lai et al., 2019).

The insights derived from EEG studies can greatly influence SEO and interface design. By understanding patterns of attention and engagement, designers and SEO experts can create more user-centric interfaces that better align with cognitive capabilities and preferences. This alignment not only boosts usability but also enhances the efficiency of information retrieval (Mladenović et al., 2022).

The field of EEG in web search has been significantly advanced by several key researchers. For instance, Yashar Moshfeghi stands out with 8 publications that offer foundational insights into the use of EEG for relevance detection and information retrieval. Other notable contributors include Giulio Jacucci and Zuzana Pinkosova, both of whom have published 4 articles each. Their consistent efforts explore the link between EEG and user behaviour. Contributions from these authors create a solid basis for systematic reviews, leading to a focused and comprehensive understanding of methodologies and findings in this specialised area (Gwizdka, 2018; Jacucci et al., 2019; Moshfeghi & Jose, 2013; Pinkosova et al., 2023a).

Finally, the review identifies notable gaps in current research, particularly regarding the limited examination of diverse user populations and real-world scenarios. Future studies should emphasise inclusivity, as well as exploring the experiences of users with varying cognitive abilities and addressing the complexities of dynamic online environments. Additionally, leveraging advanced machine learning algorithms for feature extraction and signal analysis could further enhance the predictive capabilities of EEG in this field.

One of the limitations of this review is noted to be the variety of platforms included in the studies. "Web search" was defined to encompass all kinds of systems, ranging from Google and Yahoo to bespoke experimental search engines and browser-based BCI interfaces. Differences in default layout, interaction mode, and user population are introduced by each platform. It is recognised that variations in platforms can affect cognitive load, determine relevance, and influence the interpretation of EEG signals. While trends in cognitive processes were found across studies, it should be noted that comparisons between studies should be moderated by these contextual variables. It is suggested that future studies could employ some standardisation, or at least an explicit platform type category in data analysis.

This review highlighted that, although EEG studies have made strides in exploring cognitive load, attention, and relevance during the search process, and the relationships with neural correlates of these various components, these studies indirectly address the more central issue of how users formulate intentions and ultimately assess satisfaction. Additionally, the studies shared commonalities regarding ERP component analysis related to engagement (P300) and decision-making (alpha-band suppression). However, it's important to note that the EEG-based studies predominantly involved small sample sizes, utilised varied EEG recording devices, and employed simplified search tasks, which limits their generalisability to real-world search contexts.

Future research should focus on the following areas:

1. Integrating EEG data with other data types (e.g., eye tracking and clicks) to develop a multimodal model of user intention;
2. Creating search tasks that resemble realistic behaviours more closely;
3. Investigating adaptive systems that can respond to the user's mental state in real-time;
4. Expanding the diversity of user populations to enhance representativeness.

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Appendix A

The Research Included in the Systematic Review

No.	Resource	Methods	Sample	Results	Insights
1	Xu et al. (2009)	SSVEP-based system. PSD threshold method for EEG data analysis.	10 subjects	A practical application for Google search, which involved character input and cursor control, was designed and tested on this system.	EEG is used in web searches through a brain-actuated HCI that detects SSVEP, enabling character input and cursor control. This allows users to perform Google searches effectively without traditional input devices.
2	Antonenko et al. (2010)	EEG. Development of a custom framework for adding missing semantics to Java objects.	–	EEG can measure cognitive load in real-time. EEG can detect subtle fluctuations in cognitive load.	EEG can measure cognitive load during web search tasks, detecting fluctuations in cognitive activity as users access hyperlinks. This continuous measurement helps evaluate the effectiveness of web design and instructional interventions, enhancing understanding of cognitive processes in online learning contexts.
3	Gwizdka & Cole (2011)	EEG for cognitive state detection: Analysed brain activity patterns, focusing on identifying cognitive workload and engagement during information retrieval tasks. Eye tracking: Captured gaze position, fixation duration, and saccadic movements to correlate visual attention with task complexity.	32 participants	EEG features like alpha and theta power successfully distinguished between high and low cognitive workload states. Eye-tracking metrics, such as fixation duration and scan path length, aligned well with user difficulty in task completion.	The study showed that EEG and eye-tracking features can improve adaptive information systems by responding to user cognitive states in real time, which enhances system usability and user satisfaction.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
4	Putze et al. (2012)	Cognitive modelling. EEG.	–	The preliminary results suggest that the basic computational model is adequate and that there may be valid electrophysiological correlates of learning progress, which is a promising basis for the planned detailed analyses.	The paper explores the use of EEG to measure and predict cognitive states during search tasks. This approach allows systems to optimise information presentation according to users' cognitive resources, goals, and context, ultimately improving the effectiveness of human-computer interfaces in web search scenarios.
5	Frey et al. (2013)	Combined eye-tracking and EEG to analyse cognitive processes during information-seeking tasks on textual content.	17 participants	Significant differences in EFRP signals were observed between target and non-target words, indicating enhanced cognitive processing during goal-relevant fixations. Eye-tracking provided spatial and temporal context for EEG analysis, enhancing the accuracy of attention-related findings.	Significant differences in EFRP signals were observed between target and non-target words, indicating enhanced cognitive processing during goal-relevant fixations. Eye-tracking provided spatial and temporal context for EEG analysis, enhancing the accuracy of attention-related findings.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
6	Moshfeghi & Jose (2013)	Affective and physiological signals for implicit feedback: Explored the use of multimodal features such as EEG, eye tracking, and behavioural data to provide implicit relevance feedback during information retrieval tasks.	24 participants	Affective signals, particularly EEG, improved the precision of relevance feedback. Behavioural features, like dwell time, complemented physiological data but were less reliable on their own. Multimodal fusion enhanced prediction accuracy compared to using single modalities.	Combining emotional, physiological, and behavioural signals enhances relevance feedback mechanisms, potentially transforming search systems into adaptive platforms that dynamically align with user intentions.
7	Eugster et al. (2014)	EEG signals recorded during relevance judgments. Multi-view EEG feature representation for classification.	40 participants	EEG signals can predict relevance with 17% improvement in accuracy. High-precision classifier achieves a mean precision of 0.62 with 25% improvement.	EEG can predict the relevance of terms in web searches by analysing brain signals without requiring user-specific training. This enables automatic detection of relevance judgments, thus enhancing information retrieval systems by providing insights into cognitive processes associated with relevance during information-seeking.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
8	Allegretti et al. (2015)	Within-subject design comparing relevant and non-relevant images. EEG signal measurement during relevance judgment tasks.	20 participants	Significant variation in EEG signals between relevance and non-relevance conditions. Differences in electrode locations at different stages of relevance assessment.	The study used EEG to analyse brain signals during relevance assessments in image retrieval tasks. It identified significant differences in brain activity between relevant and non-relevant stimuli. These findings could inform the development of more effective implicit feedback systems for web searches.
9	Bansal et al. (2015)	EEG sensors to determine the user's attention level. Mapping attention level with webpage section based on scrolling percentage.	_	The paper presents the results of experiments to measure user concentration levels while browsing different web pages. The paper also describes the integration of the EEG recording system into the web browser code.	EEG is utilised in web searches to gauge user attention levels while browsing. By capturing real-time EEG data and mapping it to the sections of a webpage being viewed, this technology helps identify areas of user interest. This insight can lead to improved web design and more effective ad placement.
10	Golenia et al. (2015)	EEG data for interpreting user intent. Eye-tracking data for disambiguation of search results.	_	The paper presents a demo application that uses EEG and eye-tracking data for the disambiguation of image search results. The demo showcases the integration of sensor input into a web application.	EEG is utilised in web searches to analyse users' brain activity, helping to disambiguate ambiguous queries by determining their true intent. This integration enhances the relevance of search results, ensuring users receive images that align with their specific interests.

(continued)

The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
11	Mohedano et al. (2015)	BCI for relevance feedback. RSVP for images.	users	EEG-based feedback outperforms mouse-based feedback in retrieval tasks. Users with dataset knowledge perform better than others.	The paper examines EEG as a relevance feedback mechanism in content-based image retrieval, highlighting its ability to detect relevant objects in complex images. It suggests that EEG could improve web search relevance by capturing user engagement and preferences.
12	Porta Caubet (2015)	RSVP. Relevance feedback in image retrieval.	–	–	The paper explores the use of EEG signals for relevance feedback in image retrieval, highlighting potential applications in web search by enhancing user interaction and improving search results based on real-time brain activity, thereby tailoring content to user preferences.
13	Shovon et al. (2015)	EEG data acquisition using a 40-channel Compumedics Neuroscan Nuamps amplifier. Normalised transfer entropy (NTE) for brain network construction.	10 healthy participants	Higher connectivity density during Web search task stages (Q, L, and C) compared to baseline cognitive state (EOP). EEG data acquisition using a 40-channel Compumedics Neuroscan Nuamps amplifier.	EEG was utilised to record brain activity during various stages of a Web search task, facilitating the construction of functional brain networks. This method enabled the analysis of cognitive demands and information transfer between different brain regions while searching the Web.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
14	Slanzi et al. (2015)	Eye tracking to monitor gaze position and fixations. EEG recording to analyse brain activity and attention.	20 participants	EEG features could be used to identify salient objects on a web page. Pupil size features were discarded due to low correlation with baseline.	EEG features, especially Gamma Band RMS and EEG Variance, can identify important web objects by indicating user attention without depending on the time spent on those objects. This enhances the understanding of user behaviour during web searches and improves the effectiveness of website design.
15	Eugster et al. (2016)	EEG signals recorded during reading tasks. Prediction models compared against randomised feedback performances. Each participant performed a set of 8 reading tasks during the experiments.	15 participants	Brain activity associated with relevant words is different from irrelevant words. Prediction models can extract and utilise structured signals to infer word relevance.	EEG records brain signals while users read texts to infer relevance in web searches. This data predicts word relevance, improving document retrieval and recommendations based on users' search intentions without requiring explicit interaction.
16	González-Ibáñez et al. (2016)	Low-cost EEG sensor measures attention and meditation states. Two-stage study: snippets collection and relevance assessments.	10 participants (both graduate and undergraduate students)	Attention levels and blink intensity are higher in relevant pages. EEG sensors can identify perceived relevance in web searches.	The study investigates the use of a low-cost EEG sensor to evaluate perceived information relevance during web searches. It measures levels of attention and meditation, revealing that both attention and blink intensity are significantly higher for pages considered relevant by users.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
17	Scharinger et al. (2016)	Fixation-related EEG frequency band power analyses. Analysis of EEG alpha frequency band power.	22 healthy university students	EEG alpha frequency band power was significantly lower for the complete match search result. Decreased alpha power might reflect participants' detection of the hit.	The study employed EEG frequency band power analyses to assess web search results. It found that lower alpha power at parietal electrodes was associated with participants' ability to detect complete matches among the search results. This highlights the potential of EEG in evaluating cognitive responses during web searches.
18	Zhang et al. (2016)	Combined brain wave signals with internet services for interaction. Analysed EEG signals to associate with specific actions or ideas.	_	EEG signals are used to access internet services by focusing on words. Brain wave patterns associated with specific actions or ideas are analysed.	EEG signals can initiate web searches by analysing attention and meditation levels. By focusing on specific words or phrases, users can control internet services, such as zooming in on webpages, through BCI technology.
19	Gwizdka et al. (2017)	Eye-tracking to measure eye movements during reading. EEG to assess brain activity.	24 participants	Eye-tracking data effectively distinguishes relevant from irrelevant documents. EEG signals show a limited ability to classify relevance.	The study investigates the use of EEG for detecting cognitive processes during relevance judgments in web searches. It shows that affordable EEG devices can differentiate between relevant and irrelevant documents, thereby contributing to the understanding of user behaviour and improving information retrieval systems.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
20	He et al. (2017)	Hybrid BCI using EEG and EOG signals. Mouse control via imagined hand motion and eye blinks.	5 healthy subjects	Experimental results showed the effectiveness of the proposed method.	The study uses EEG signals to control horizontal mouse movement through the imagination of left and right-hand motions, allowing users to navigate web pages. This hybrid BCI approach improves web search capabilities by integrating EEG with EOG signals for target selection and text input.
21	Katona et al. (2017)	EEG-based BCI system for real-time brainwave monitoring. Statistical evaluation of brainwave values during media browsing.	15 participants	The mid-gamma brainwave strength is higher while watching videos containing web pages rather than looking at static pictures or reading a simple text.	EEG is utilised in web searches to track real-time brainwave variations as subjects explore various media content. This study examines the changes in brainwave strength, highlighting cognitive processes linked to browsing text, images, and videos online.
22	Martínez-Cagigal et al. (2017)	P300-based BCI using EEG signals. Odd-ball row-col paradigm for P300 evoked potentials.	16 multiple sclerosis patients and 5 healthy volunteers	Results show that multiple sclerosis patients can successfully control the BCI web browser, improving their autonomy.	The paper discusses an EEG P300-based BCI web browser that utilises the “odd-ball” paradigm to translate P300 evoked potentials into web commands, enabling severely disabled users to perform web searches effectively and autonomously.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
23	Wenzel et al. (2017)	Real-time inference from EEG and eye tracking signals. Classification of relevant words based on neural activity.	15 participants	Subjectively relevant words could be decoded online from EEG and eye-tracking signals. The average rank of the category of interest was 1.62 after reading 100 words.	The paper shows that EEG can determine the subjective relevance of words in real time, potentially improving web search by adjusting results based on user interest. This enhancement enriches interaction by using implicit information gathered from neural activity and eye movements.
24	Yehia et al. (2017)	Utilises SSVEPs. Records EEG signals with an Emotiv EPOC headset.	3 healthy subjects	Average accuracy of command detection: 86.08% ± 15.46% Fully functional in web navigation tasks.	The paper discusses utilising EEG, specifically SSVEPs, for enabling BCI web browsing. It demonstrates a functional application that allows users to navigate the internet with an average command detection accuracy of 86.08%.
25	Debue et al. (2018)	Researchers analysed user behaviour, task completion times, accuracy, and subjective feedback.	36 participants	Performance: Laptops generally provide faster task completion times due to the precision of the keyboard and mouse interface. Satisfaction: Participants appreciated the intuitive and engaging interaction of touch-screen PCs, particularly for casual browsing tasks.	These insights help design interfaces that leverage the strengths of each device, such as improving touchscreen responsiveness for text input and optimising laptops for multimedia use.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
				Preferences: While touch screens were preferred for visual tasks (e.g., image searches), laptops were favoured for tasks requiring text input and multitasking.	
26	Golenia et al. (2018)	EEG for brain signal analysis. Eye tracking for visual attention measurement.	_	The intended interpretation of ambiguous search terms was inferred correctly in 86% of cases using EEG and eye tracking signals. Eye tracking for visual attention measurement.	EEG is utilised in web searches to decode user interests by analysing brain signals in response to images. This implicit feedback enables real-time adaptation of search results, enhancing personalised user experiences in simulated image search engines.
27	Gwizdka (2018)	Eye-tracking to measure pupil dilation. Single-channel EEG for attention level assessment.	26 participants	Significant differences in pupil dilation on relevant and irrelevant web pages. Significant differences in pupil dilation on relevant and irrelevant web pages.	The study revealed significant differences in EEG alpha frequency power and attention levels during searches for health-related information. This suggests that low-cost EEG devices can effectively assess the relevance of web pages based on physiological responses.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
28	Jimenez-Molina et al. (2018)	The researchers utilised a combination of EEG, PPG, and EDA sensors to measure mental workload. Tasks were designed to induce varying levels of cognitive demand. Data were analysed to classify 4 distinct levels of mental workload.	53 participants	Workload Levels: Web browsing tasks can be categorised into four workload levels based on sensor readings. Efficiency: The combination of EEG, PPG, and EDA sensors significantly improved the classification accuracy of mental workload.	Continuous assessment of mental workload provides valuable insights into user engagement and cognitive strain during online activities. These findings can be applied to optimise web interfaces and tailor browsing experiences to users' cognitive states.
29	Al-Samarraie et al. (2019)	Participants were exposed to reading tasks in both single-column and multiple-column formats. EEG data were collected to assess cognitive load, focusing on brain activity patterns related to attention and workload.	27 participants	Single-column layouts resulted in lower cognitive load compared to multiple-column layouts, which were associated with higher attentional demands.	These results suggest that single-column designs are more effective for tasks requiring sustained reading and comprehension.
30	Jacucci et al. (2019)	Online implicit relevance feedback from EEG and eye movements. User-specific classifier for predicting keyword relevance.	16 participants	Classification performance was significantly better than random for 13 out of 16 participants. Online relevance predictions had averaged AUROC values of 0.53.	EEG is used to compute online implicit relevance feedback in web searches by measuring brain activity. When combined with eye movements and explicit feedback, this approach enhances interactive intent modelling and improves classification performance in realistic information retrieval tasks.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
31	Lai et al. (2019)	EEG for brainwave data collection. Empirical mode decomposition (EMD) and back-propagation neural networks (BPNN).	_	Accuracy rate: 56.6%, precision rate: 50%, recall rate: 60.4%. Brainwave-based recommendations outperform random recommendations (12.5% accuracy).	EEG is used in web searches to analyse users' brainwave signals. It identifies preferences through EMD and artificial neural networks, thus enhancing recommender systems with personalised suggestions based on users' cognitive responses while browsing.
32	Lin et al. (2019)	Combined SSVEP from EEG and eye-tracking data. Utilised WebSocket API for server-client communication.	_	Average overall accuracy of 88.5% achieved by subjects. Copy-spelling accuracy of 100% for all subjects.	EEG is used in a hybrid BCI web browser to capture SSVEP. This technology enables users with severe motor impairments to perform web searches by combining EEG signals with eye-tracking data, allowing for natural interaction without a mouse.
33	Nel et al. (2019)	BCI to measure emotions. Pre-test and post-test questionnaires for data collection.	_	The captured emotional data, as well as pre-test and post-test questionnaire data, suggest that the different search engines and search terms had an influence on the emotions of a participant during searches with ambiguous search queries.	The study employed a BCI to measure emotional metrics such as Long-Term Excitement, Short-Term Excitement, Engagement, Meditation, and Frustration using EEG technology while participants conducted ambiguous web searches across various search engines.

(continued)

The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
34	Pinkosova & Moshfeghi (2019)	Brain imaging techniques like EEG and fMRI. Analysis of physiological and behavioural signals.	–	Investigates user relevance through physiological and behavioural signals. Aims to enhance understanding of Saracevic's relevance model.	EEG has been used to identify neural signatures during relevance processing in web searches. This research has revealed time intervals of implicit judgments and significant differences in brain activity between relevant and non-relevant information, thus enhancing the understanding of user-system interaction and relevance assessment.
35	Sarraf (2019)	Search Exploration Stage: Marked by high cognitive demand and emotional uncertainty, with neural markers indicating heightened attentional processing. Formulation Stage: Demonstrated a shift towards cognitive clarity and reduced uncertainty, reflected in neural activity associated with decision-making. Collection Stage: Associated with task satisfaction and focused engagement, with lower cognitive load compared to earlier stages.	48 students from 2 universities	Neurophysiological tools such as EEG and other psychophysiological measures were employed to study brain activity. Participants performed tasks corresponding to ISP stages, allowing the identification of specific cognitive and emotional patterns during each stage.	Provides a deeper understanding of the interplay between cognition and emotion in information-seeking behaviours. Supports the development of user-centred systems that account for emotional and cognitive states during information searches.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
36	He et al. (2020)	EOG-based button selection method for target selection. Combined EEG and EOG for mouse control.	10 healthy subjects	Superior performance was achieved compared to previous BCI systems.	The paper discusses an asynchronous hybrid BCI system that uses EEG signals for mouse control during web browsing. Specifically, it utilises left- and right-hand motor imagery-related EEG to manage horizontal mouse movement, allowing users to navigate the internet without physical actions.
37	Pinkosova et al. (2020)	EEG for brain activity assessment. Graded relevance judgements in a Question Answering Task.	24 participants	Significant differences in ERPs for graded relevance levels were observed. Attentional engagement, semantic mismatch, and memory processing influence responses.	The study used EEG to examine brain activity linked to varying levels of relevance during a question-answering task. It revealed significant differences in ERPs for high, low, and no relevance. These findings can help inform the design and evaluation of web search systems.
38	Chen et al. (2022)	Brain signal decoding for user satisfaction feedback. Query suggestion powered by Sogou Inc API. System re-ranks search results based on user satisfaction feedback.	–	Users can search without a mouse/keyboard, providing real-time feedback. System re-ranks search results based on user satisfaction feedback.	EEG is used in the BMSI system to decode brain signals for formulating queries and interacting with search results, allowing users to perform web searches without traditional input devices. It captures real-time user satisfaction and context to improve the search experience.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
39	Michalkova et al. (2022)	EEG. ERP analysis.	14 participants	Early brain activity indicates awareness before conscious realisation. Participants showed a strong preference for resolving knowledge gaps.	The effectiveness of EEG in capturing brain activities during complex cognitive processes in web search lies in its fine-grained temporal resolution. It helps in understanding the realisation of information needs, memory retrieval, and user behaviour, thus enhancing the design of information retrieval systems.
40	Pinkosova et al. (2023b)	Data-driven approach using EEG. Measurement of neural activity in response to relevance assessment.	24 participants	Significant variation in neural activity associated with relevance assessment. Identification of previously unreported P100 component related to attention and working memory.	The study used EEG to measure neural activity during participants' binary relevance assessments in a question-answering task, revealing significant differences in EEG signals associated with cognitive components like P300/CPP, LPC, and a previously unreported component.
41	Pinkosova et al. (2023a)	EEG to measure neural activity. Relevance assessments during a Question and Answering Task.	24 participants	SPK influences relevance assessment and cognitive processes. Significant differences in brain activity based on SPK.	The research used EEG to assess neural activity during relevance evaluations in a question-and-answer task. This study revealed how SPK impacts cognitive processes such as attention, semantic integration, and decision-making in web search relevance assessments.

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The Research Included in the Systematic Review (contiune)

No.	Resource	Methods	Sample	Results	Insights
42	Ye et al. (2023)	BCI-based relevance feedback integration. Combination of pseudo-relevance and implicit signals.	21 participants	Incorporating brain signals improves the relevance feedback (RF) framework performance significantly. Brain signals excel in hard search scenarios with missing feedback.	EEG can monitor brain activity during web searches, offering direct and unbiased feedback on relevance. This method improves retrieval performance by combining brain signals with pseudo-relevance and implicit signals. It is especially effective in challenging search situations where traditional feedback may be insufficient.
43	Michalkova et al. (2024)	EEG recordings captured brain activity as participants performed search tasks requiring introspection about their level of knowledge. Behavioural data and subjective self-reports complemented EEG data to link cognitive states with FOK experiences.	24 healthy university students	FOK shares characteristics with *Anomalous States of Knowledge (ASK)*, reflecting a mismatch between what is known and what is sought. Variability in information needs and FOK realisation is influenced by task complexity and individual cognitive strategies. EEG data revealed specific neural patterns linked to high or low FOK states, offering the potential to develop adaptive search systems tailored to user needs.	Insights enhance understanding of user behaviour in information retrieval and inform the design of systems capable of responding to cognitive states during search activities.

Appendix B

Abbreviations

AUROC – Area Under the Receiver Operating Characteristic Curve	HCI – Human-computer interface
BCI – Brain-computer interface	ISP – Information seeking process
BMSI – Brain-Machine Search Interface	LPC – Late Positive Component
CPP – Centro-Parietal Positivity	P300 – A specific ERP component
EDA – Electrodermal activity	PPG – Photoplethysmogram
EEG – Electroencephalography	PSD – Power spectral density
EFRP – Eye fixation-related potential	RMS – Root mean square
EOG – Electrooculography	RSVP – Rapid serial visual presentation
ERP – Event-Related Potential	SPK – Self-perceived knowledge
FOK – Feeling-of-knowing	SSVEP – Steady-state visual evoked potential

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腦波圖在網路搜尋研究中的應用：針對樣本大小、活躍作者和研究結果的系統性回顧

The Application of EEG in Web Search Research: A Systematic Review on Sample Size, Active Authors and Results

Mahsa Torabi[1]

摘　要

儘管腦波圖（EEG）在網路搜尋研究中的應用日增，但樣本量少、研究方法龐雜且普遍性有限等問題依然存在。本研究採用系統性回顧，遵循PRISMA框架，探討EEG在網路搜尋研究的應用，在多個學術資料庫搜索並篩選相關文獻後，針對樣本大小、研究方法和遭遇的挑戰進行分析。結果顯示，EEG研究的樣本量通常在10到24人之間，主要受限於資源。研究者面臨的挑戰包括生物假象、情緒和認知狀態的複雜性，以及小樣本量導致的代表性不足，而設備品質和方法一致性等問題也增加了研究難度。整體而言，EEG在網路搜尋研究中具有龐大潛力，但仍需解決上述挑戰，以提升研究結果的穩健性和適用性；本研究建議未來應著重於改進研究方法、探索創新技術，克服現有侷限。

關鍵字：腦波圖、網路搜尋、系統性回顧、資訊行為

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