Report on the 3rd Workshop on NeuroPhysiological Approaches for Interactive Information Retrieval (NeuroPhysIIR 2025) at SIGIR CHIIR 2025

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Abstract

The International Workshop on NeuroPhysiological Approaches for Interactive Information Retrieval (NeuroPhysIIR'25), co-located with ACM SIGIR CHIIR 2025 in Naarm/Melbourne, Australia, included 19 participants who discussed 12 statements addressing open challenges in neurophysiological interactive IR. The report summarizes the statements presented and the discussions held at the full-day workshop.

Date: 27 March 2025.

Website: https://neurophysiir.github.io/chiir2025/.

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1 Introduction

The International Workshop on NeuroPhysiological Approaches for Interactive Information Retrieval (NeuroPhysIIR'25) [Gwizdka et al., 2025] aimed to bring together researchers from information retrieval (IR), human-information interaction (HII), human-computer interaction (HCI), cognitive neuroscience, and related fields, to foster cross-disciplinary collaboration and accelerate progress in neurophysiologically informed Interactive Information Retrieval (IIR) research. This research utilizes measures such as facial-expression analysis, eye tracking, and peripheral indices of arousal (electrodermal activity/galvanic skin response, electrodermal activity/galvanic skin response (EDA/GSR), and photoplethysmography, PPG) to quantify human reactions to information. Brain–computer-interface (BCI) recordings likewise serve this purpose, employing electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) to capture real-time cortical dynamics and reveal the neural correlates of cognitive and affective processing.

Topics of interest include (but are not limited to):

- Resources, methodologies, and/or best practices for neurophysiological IIR;
- Replicability and reproducibility of experiments using neurophysiological signals;
- Using neurophysiological measures for evaluation;
- Using neurophysiology as a feedback channel;
- BCI for information retrieval and generation; and
- Measuring user experience during human-information interaction using neurophysiological methods.

The full-day workshop was co-located with ACM SIGIR CHIIR 2025[1] and took place in Naarm (Melbourne), Australia, on 27 March, 2025. We had a total of 19 (16 in-person, 3 online) participants. The workshop started with an overview given by the organizers. Each co-organizer gave a lightning talk showcasing the aspects of their work specific to neurophysiological IIR. The main activity of the workshop consisted of the discussion of statements submitted by participants. A total of 12 statements were presented, including an extra one pitched later in the workshop (Section 2). The workshop concluded with a discussion aimed at identifying open challenges and key research questions to shape future directions in the field (Section 3).

2 Statements

We issued a Call for Statements[2] to assist in curating the topics for discussion during the workshop. We adopted the template proposed by Spina et al. [2021] for the Future Conversations workshop at CHIIR'21. This model lowered disciplinary barriers, actively drawing participants from across cognitive science, information science, wearable computing, and other fields.

Statements consisted of approximately two paragraphs drafted to address each of the following five points:

Problem. Who is it that has a problem, or an opportunity, with neurophysiological IIR? Please tell us something about a person, group of people, or a situation.

[1] https://chiir2025.github.io/

[2] https://neurophysiir.github.io/chiir2025/submission/

What are the problems or opportunities there? Please give as many examples and as much detail as possible – at least a paragraph.

Why is the problem important and timely?

Goal. What should the research community be doing to help? Please give as many examples and as much detail as possible.

State of the art. A brief overview of where we are at now, and in which research field/domain.

What do we already know? What are the one or two key resources we already have?

Next Steps. List any resources, collaborations, research goals, or anything else that may help along the way.

Ethical Considerations. Please discuss any ethical considerations that may be relevant. For example, privacy and confidentiality of data.

The 12 statements discussed during the workshop are detailed below.

2.1 Quantifying Cognitive Biases Using Physiological Sensing

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2.1.1 Problem

Pervasive devices allow humans to access information anytime and anywhere. However, the sheer amount of information available from devices is far beyond human limited cognitive and memory bandwidth. Humans also need to make fast decisions based on information that is often ambiguous. Therefore, humans apply mental shortcuts or heuristics to effectively make decisions under such constraints. These shortcuts can lead to systematic error in judgment or the so-called cognitive biases. These biases are an integral part of human mental states, allowing humans to act and thrive in the real world.

In the context of information search and consumption, cognitive biases influence problematic behaviors, such as selectively seeking information that confirms one's beliefs, over-relying on search engine's results, or judging non-relevant items as relevant [Azzopardi, 2021]. Recently, cognitive biases have also exacerbated the spread of misinformation as these biases skew the way individuals perceive information on the Internet and make them fall victim to fake news.

Quantifying the effects of cognitive biases will help identify such biases and accurately deploy interventions to mitigate their adverse effects (e.g., through nudging or education prompts). However, these biases are not always pronounced as they are subject to a plethora of factors, such as user characteristics, the presentation of information, or the interaction context [Boonprakong et al., 2025]. Moreover, cognitive biases generally occur without the awareness of users. The unconscious and complex nature of cognitive biases warrant a challenge of how cognitive biases can be reliably and objectively quantified.

Previous research has employed self-report (e.g., questionnaires) and behavioral measures (e.g., screen behavior or dwelling time) to quantify cognitive biases. However, self-reports are prone to subjectivity and behavioral measures do not reliably indicate cognitive biases. On the other

hand, physiological signals present a feasible solution to the quantification of cognitive biases. Known as “a window to our mind”, physiological sensing has been regarded as a non-intrusive, more objective way to quantify human mental states, including cognitive biases.
Despite its potential, quantifying cognitive bias through physiological sensors poses several challenges. Like measures of cognitive bias, physiological signals are vulnerable to task-related noise and confounds, such as variations in device or electrode placement [Boonprakong et al., 2023; Ji et al., 2024b; Kingphai and Moshfeghi, 2024, 2021]. Thus, the physiological expression of cognitive biases is weak and difficult to detect by wearable, non-intrusive devices.

2.1.2 Goal

We need to bring together experts and practitioners across the fields of IR, HCI, neuroscience, and cognitive science to find a common ground for quantifying cognitive biases using physiological sensing. Taken together, we will draft a blueprint for study designs that allow reliable quantification of cognitive biases.

2.1.3 State of the Art

There is a lack of research that investigates the use of physiological sensing to quantify cognitive biases in HII. An early example is Boonprakong et al. [2023], who shows that hemodynamic activity measured through fNIRS is a feasible measure of cognitive bias while reading diverse opinions, while only a weak trend was found for EDA signals. Moreover, Ji et al. [2024b] explore the use of EEG and EDA to quantify cognitive biases in conversational search.

2.1.4 Next Steps

In this workshop, I propose some motivating questions as follows:

- What are promising scenarios of HII where cognitive biases manifest and become potentially problematic?
- What are specific cognitive biases manifesting during HII? What elements of HII trigger them? Do these cognitive biases confound each other?
- What are the study designs that will elicit cognitive biases? How can we minimise or control confounding factors in HII?
- What physiological measurements are compatible with such studies? What part of the human body does allow placement of physiological sensors?
- What are considerations when processing and analyzing physiological signals collected during HII?

2.1.5 Ethical Considerations

The ability to quantify cognitive biases will bring about effective mitigation of cognitive bias. However, it also suggests a way to infer and utilise such biases to steer and manipulate people’s behavior and decision-making. The Cambridge Analytica scandal showcases that people’s personal traits and tendencies can be modeled and used to steer opinion-making (i.e., the 2016 US presidential election). The quantification of cognitive biases may face legal restrictions (e.g., for collecting personal information) especially in the regions with data protection laws in effect.

2.2 When Should I Stop Searching? Exploring Neuro-Correlates of Information Need Satisfaction in Online Search

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2.2.1 Problem

Online search has long been the primary conduit for search. The rich information resources of online search enable users to make better decisions than traditional information search (IS) [Cole, 2011]. However, this "limitless" information, especially provided by the AI-integrated search engine, often requires individuals to spend more time and effort to decide when to stop searching [Simon, 1996], which can lead to a high mental workload or even mental overload, resulting in a poor user experience or even a failed search. Although research indicates that more information does not always improve search outcomes [Simon, 1996; Prabha et al., 2007], the quantity of online information continues to grow rapidly [Rydning et al., 2018]. Despite this, few studies have focused on understanding how users decide to stop searching [Fox et al., 2005; Al-Maskari and Sanderson, 2010; Browne and Walden, 2021; Moshfeghi et al., 2019; Pinkosova et al., 2020].

2.2.2 Goal

To develop an effective IS system that signals to users when to stop, it is crucial to understand when their information need is satisfied. This is a phenomenon that remains something of a 'black box' [Taylor, 2015], as individuals cannot predict what exactly will fulfill their needs.

2.2.3 State of the Art

Previous studies have used both implicit (e.g., dwell time [Fox et al., 2005], click-through rate [Fox et al., 2005]) and explicit (e.g., self-reports [Al-Maskari and Sanderson, 2010]) measures to identify indicators of information need satisfaction, but these methods fall short of capturing the full cognitive processes behind stop decisions. Neuroscientific techniques, such as functional Magnetic Resonance (fMRI) [Paisalnan et al., 2021a, 2022] and electroencephalography (EEG), offer deeper insights by mapping brain activity linked to these decisions, revealing distinct brain areas activated when users stop versus continue searching [Browne and Walden, 2021; Moshfeghi et al., 2019, 2016; Pinkosova et al., 2020].

2.2.4 Next Steps

The high cost and sensitivity to movement, limit fMRI and EEG's practical application in real-world settings. fNIRS, by contrast, presents a more flexible and movement-tolerant alternative, making it a promising tool for future research. In addition, the tasks used for the study should be considered to use real-world search tasks rather than simulated paradigms like puzzle games.

2.2.5 Ethical Considerations

In addition to standard ethical considerations for studies that do not involve brain activity measures – such as informed consent, data privacy, and the right to withdraw – there are additional aspects to address when using neuroimaging technologies to explore cognitive processes related to online search behaviors. First, participants must be fully informed about the study's purpose and how brain imaging techniques will be used. This helps minimize any concerns participants might have about their data being compromised, which could influence their behavior during the study. Additionally, although fNIRS is a non-invasive technique, participants should be monitored throughout the study to ensure their comfort and safety. The study should be paused or stopped if any signs of discomfort or distress are observed.

2.3 Characterizing Uncertainty and Curiosity in Information Seeking Behavior Using Neurophysiological Signals

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2.3.1 Problem

Information seeking begins with an understanding that there is something we do not know [Belkin, 1980]. However, the motivations of starting search behavior is poorly understood. Previous studies have indicated that such motivations are driven by states of curiosity or uncertainty, which can be linked to individuals different personality traits – some seeking knowledge for enjoyment while others do so to reduce anxiety [Jach et al., 2022]. This understanding is important for designing adaptive search systems that accommodate diverse user needs. The challenge is to develop IR systems that can distinguish between different motivations for searching and personalize interactions accordingly. For example, an anxious user seeking reassurance may require a different search experience than a curiosity-driven user exploring for enjoyment.

2.3.2 Goal

To leverage neurophysiological signals—such as eye-tracking, EDA, and EEG-to uncover the motivations behind information-seeking behavior and predict associated personality traits.

2.3.3 State of the Art

Current research has identified links between personality traits (e.g., the Big Five Inventory [McCrae and Costa Jr., 1996]) and information seeking behaviors [Al-Samarraie et al., 2017]. In particular, openness is associated with curiosity-driven search, whereas neuroticism aligns more closely with uncertainty intolerance [Jach et al., 2022]. Neurophysiological signals such as ECG and EEG have also been used to assess cognitive and emotional states during search tasks [Berkovsky et al., 2019; Ji et al., 2024a; McGuire and Moshfeghi, 2024; Michalkova et al., 2024].

2.3.4 Next Steps

1. Design user studies to explore these dynamics
2. Investigate the motivation categories for information seeking
3. Understand the correlations between motivations and neurophysiological signals
4. Analyze different personality traits in information seeking with neurophysiological signals

2.3.5 Ethical Considerations

The use of neurophysiological devices can cause ethical concerns regarding data privacy. Ensuring user consent, data security, and transparency in how physiological data influences search outcomes is important.

2.3.6 Summary

Understanding the correlation of personality, uncertainty, and curiosity in information seeking behavior is important for the adaptive IR systems. By integrating neurophysiological signals, we can better predict user personality traits and motivations to make IR system more adaptive and personalized.

2.4 Toward Innovative Neurophysiological Methods for Search Interface Evaluation

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2.4.1 Problem

In IIR, standard practice has typically relied on user logs and post-task questionnaires to evaluate systems. While valuable, these methods can offer only a limited view of the user experience. In particular, post-task surveys tend to emphasize the final or most memorable events, inadvertently overlooking the full range of affective and cognitive shifts that occur during the search process [Pirmoradi and Hoeber, 2025]. This limited lens may miss subtle affective and attentional shifts, such as when a particular interface feature sparks frustration or delight. As interfaces become more complex, particularly in exploratory search or cognitively demanding settings, there is a growing need to innovate how we measure, interpret, and act upon user responses. The challenge lies in unifying multiple data sources such as eye tracking, facial expressions, and other neurophysiological signals, into a coherent evaluation framework. Researchers struggle with synchronization and meaningful interpretation, while practitioners lack a clear roadmap for real-world application.

2.4.2 Goal

The main goal is to expand and refine interface evaluation by leveraging a multimodal approach, thereby providing a deeper understanding of searchers' underlying cognitive and emotional states. In particular, neurophysiological measures serve as a complementary layer to conventional metrics by helping researchers and designers pinpoint how specific interface components contribute to positive or negative user experiences [Pirmoradi and Hoeber, 2025]. This includes identifying which features elicit heightened engagement or confusion, capturing the exact moment a design element fosters emotional responses (whether negative or positive), and enabling data-driven improvements that enhance usability, reduce cognitive load, and ultimately improve the overall user search experience.

2.4.3 State of the Art

Early work in neurophysiologically informed IIR initially concentrated on verifying the effectiveness of emotion detection approaches during the search process [Pirmoradi and Hoeber, 2025]. Building on this foundation, subsequent research integrated eye-tracking data with feature use and real-time emotional responses [Pirmoradi et al., 2025], thereby advancing the field by capturing not only active interactions, where users look at a feature and use it, but also passive interactions, in which users look at a feature and choose not to use it. This innovative focus on passive interactions offers a state-of-the-art perspective that uncovers the emotional aspects in the choice not to interact with specific interface elements, highlighting the positive or negative reactions that standard log analysis cannot capture. By analyzing user interactions at a feature level and integrating rich neurophysiological signals, this approach offers deeper insights into user experience than would be possible through post-task surveys or log-based measures alone. However, standardized guidelines for such multimodal methods remain sparse, and current studies often rely on controlled settings requiring specialized hardware, posing challenges for reproducibility and widespread real-world adoption.

2.4.4 Next Steps

Future approaches must establish clear standards for integrating eye tracking data, facial expressions, peripheral physiology, and interaction logs so that these distinct data sources can be aligned in a meaningful way. At the same time, open-source software should be developed or refined to automate the detection of patterns across these streams, particularly for highlighting the moments when interface elements trigger emotional responses, whether they be used passively or interactively. Finally, to broaden the ecological validity of interface evaluations, methods need to be adapted for use not only in specialized laboratories but also in more naturalistic settings.

2.4.5 Ethical Considerations

- Data Privacy: Physiological signals are sensitive, and so, transparent consent procedures and secure data storage are critical.
- Bias and Misinterpretation: Emotion recognition models may have biases based on demographics; research should aim for fair and inclusive models.

2.5 Robust Emotion Prediction in Human-AI Collaboration for High-Stake and Dynamic Environment

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2.5.1 Problem

In high-stakes environments, such as bushfire emergency response [Lim, 2021], trust in AI agents is crucial for effective decision-making. This trust depends on the AI's ability to use real-time human emotions captured through physiological data to adapt its decisions. However, a significant challenge arises from cross-subject variability, which makes it difficult to develop a generalized emotion prediction model that performs reliably across different individuals. As a result, AI systems struggle to interpret emotions accurately and provide adaptive, explainable responses. Addressing this challenge is essential for building trust in AI and ensuring its effectiveness in highly sensitive, time-critical scenarios.

2.5.2 Goal

This research aims to develop a robust emotion recognition model that addresses cross-subject variability in physiological data. The goal is to develop a generalized solution for real-time emotion prediction that enables AI agents to receive immediate human feedback and improve adaptability and trust.

2.5.3 State of the Art

Current methods for addressing cross-subject variability, such as domain adaptation, are mostly limited to offline settings [Kirkpatrick et al., 2017; Ozyurt et al., 2023]. These approaches rely on training models on large, static datasets and are not directly applicable to dynamic scenarios. Online Continual Learning (OCL) framework has also been proposed to address the inter-subject variability [Duan et al., 2024]. However, existing methods often suffer from catastrophic forgetting, where models forget previously learned information when exposed to new, continuously evolving data.

2.5.4 Next Steps

To overcome the limitations of current methods, we propose leveraging OCL framework that dynamically updates the model in real-time as new data arrives. Specifically, we aim to exploit second-order information, particularly the Hessian matrix, to regularize the loss function during training. The Hessian matrix determines the curvature of the loss landscape [Pennington and Worah, 2018]. In an OCL setting, approximating the Hessian diagonal terms [Becker and Lecun, 1989; Schraudolph, 2001] provides valuable insights into model sensitivity to the current data stream. Large Hessian values indicate high sensitivity of specific model parameters [Ahmad et al., 2023], which can be used to regularize learning and prevent important parameters from drifting away from a generalized objective. This approach facilitates knowledge retention while enabling adaptation to new data.

2.5.5 Ethical Considerations

Research in the areas of physiological data analysis usually involves ethical considerations focusing on the privacy and consent of individuals providing physiological data. However, this research aims to evaluate methodologies using publicly available datasets [Miranda-Correa et al., 2021] for preliminary findings. Moreover, transparency in AI decision-making, particularly in high-stakes environments, must align with ethical standards to ensure accountability and trust.

2.6 An Eye-tracking Study of How Users are Influenced to Search in the Era of GenAI

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2.6.1 Problem

Search interfaces are constantly evolving, yet limited research has examined these changes. The design space for search engine interfaces is vast, but interaction techniques and user interfaces for information access with LLMs remain under-researched and poorly understood. Between 2020 and 2024, 750 preprints related to LLMs were published on arXiv in the field of Information Retrieval, with only 22 mentioning "user interface" in their abstracts [Aliannejadi et al., 2025]. Existing literature largely focuses on technical aspects of GenAI, with limited research on user interaction with GenAI.

2.6.2 Goal

This study will contribute to filling this gap by understanding user behavior, preferences, and cognitive effort in human-AI interactions. Specifically, the goal of this research is to explore how users seek information in the era of GenAI via a series of user eye tracking lab studies. These studies will be conducted to compare traditional search engines with GenAI-based systems. Based on these lab studies, the aim is to develop new methods that better fulfill users' information needs.

2.6.3 State of the Art

Several eye-tracking studies have examined gaze patterns in search engine interfaces [Abualsaud and Smucker, 2019; Fu et al., 2023; Liu et al., 2022], but none have explored LLM-based interfaces. Abualsaud and Smucker [2019] analyzed user behavior on search-engine results pages (SERP) across desktop and mobile, categorizing users as 'exhaustive' (who review multiple results) and 'economic' (who focus on top-ranked links). They found that strong queries led to higher click-through rates, while weak queries prompted reformulation. Users demonstrated an internal sense of query quality, influencing their behavior. Liu et al. [2022] examined fixation patterns and search performance, using AOI-based attention measures and NDCG. Their results showed a positive correlation between gaze on abstract elements and search performance, with challenging tasks linked to higher accuracy. However, findings may be limited due to interface design and participant demographics, primarily from biomedical backgrounds.

2.6.4 Next Steps

This work contributes to the larger goal of understanding and improving search experience in the Era of GenAI. Despite ongoing research on human-GenAI interactions, many open questions remain. We believe GenAI has the potential to revolutionize how users interact with traditional search engine results, challenging the classic "ten blue links" model. Another key aspect we plan to investigate is when users choose traditional search engines over GenAI conversational search systems or AI-powered web-search options. Part of our future work will be to design methodologies to carry out studies regarding what users find more usable and trustworthy in these systems. We then plan to provide recommendations that benefit society in navigating the evolving landscape of search in the era of GenAI. A challenge we expect to face is determining which user and external variables to account for and what framework to follow.

2.6.5 Ethical Considerations

This study has received ethics approval from RMIT University for conducting eye-tracking experiments. The approval ensures that participant data is collected and handled following ethical research guidelines.

2.7 Using Eye-Tracking to Enhance Interactive Learning in Online Education

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2.7.1 Problem

Due to the global pandemic and the increasing integration of technology into education, there has been a rapid shift to online learning platforms, spanning from K-12 to higher education. Online education primarily relies on video conferencing software for delivering lectures and Learning Management Systems (LMS) to provide course materials remotely. During online learning, students engage with course materials through searching as learning, where they actively explore, query, and navigate various resources to better understand the subject. However, the systems used in online education have struggled to effectively capture important cognitive aspects of the learning process, such as attention, confusion, or frustration [Jindal et al., 2021; Vinnik and Pryadko, 2023; Chase and Yan, 2017], thus leaving a gap in understanding how well students are processing the material. As a result, these platforms lack the capability to assess or respond to students' cognitive states in real-time, making it challenging to optimize and personalize the learning experience.

2.7.2 Goal

The field of eye-tracking is well-established, with extensive research on its ability to assess visual attention [Milisavljevic et al., 2019; Wisiecka et al., 2022b,a; Krukar et al., 2020; Orlov, 2017; Krejtz et al., 2023, 2016, 2017, 2014], cognitive load [Jamal et al., 2023; Kasprowski et al., 2024; Sievert et al., 2018], and emotional responses [Kasprowski et al., 2024; Fuentes et al., 2021; Fu et al., 2024; Yang et al., 2023]. This technology has proven valuable in measuring user engagement and attention levels [Prameswari and Rahmi, 2024; Jaiswal et al., 2023; Ferrato et al., 2024], and can be performed using web cameras, making it easily accessible to the majority of users on online education platforms [Guan et al., 2022; Johnson and Strauch, 2023]. For example, Šola et al. [2021] utilized such technologies to engage facial coding and eye-tracking techniques for the study of students' attention, motivation, and interest in an online classroom. This research demonstrates the potential of integrating eye-tracking into LMS to provide real-time feedback on students' cognitive states and enable dynamic content adjustments based on students' neurophysiological responses.

The ultimate goal is to develop intelligent adaptive learning platforms that can interpret eye-tracking data and modify content based on real-time cognitive insights. Researching these adaptive capabilities could enhance student engagement and improve the overall learning experience. For example, if eye-tracking data indicates signs of distraction or mind-wandering, the system could adjust the lesson by introducing interactive elements or altering the pace. This would create a more responsive and adaptive learning environment, where instructional strategies continuously align with students' real-time cognitive states.

2.7.3 State of the Art

Several recent studies have explored the use of AI-driven eye-tracking technology to monitor cognitive aspects of online learning. For example, Šola et al. [2024a] utilized an AI-powered eye-tracking system to assess cognitive demands in video lectures, providing insights into students' cognitive processes. Christoforou et al. [2024] combined EEG and eye-tracking data to analyze student engagement with Science Technology, Engineering, and Mathematics video content, whileŠola et al. [2024b] demonstrated how eye-tracking AI could predict preferences in college magazines, both online and in PDF format, by assessing attention and cognitive load. Additionally, Liu et al. [2020] investigated how eye-tracking could detect emotional states in online learning. These studies highlight the growing interest in using neurophysiological responses to improve the online learning experience.

Despite these advancements, no adaptive learning platform has yet been developed that integrates neurophysiological data to dynamically adjust content or presentations based on students' cognitive states in real-time, with the goal of enhancing engagement and learning outcomes.

The work presented by Peng and Fu [2022] takes a similar approach by utilizing data mining and analysis techniques to identify learner behaviors, cognitive levels, learning styles, interactive behaviors, and social characteristics. While this method successfully recognizes diverse online learning patterns and improves personalized learning resource recommendations, it does not yet incorporate neurophysiological data for real-time adaptive content adjustments. Integrating such data could further optimize the learning experience by aligning content and pacing with students' immediate cognitive states.

2.7.4 Next Steps

The next steps involve further refining algorithms for real-time processing of eye-tracking data to accurately detect cognitive states such as attention, confusion, frustration, and engagement. Extensive research is needed to validate these algorithms across diverse student populations, ensuring they are free from biases and provide results with higher accuracy.

Additionally, exploring methods for automatically adjusting learning content based on real-time cognitive data is essential. This could involve dynamically altering the lesson pace, incorporating interactive elements, or pausing to initiate discussions. It is important that these adjustments are seamless and do not disrupt the flow of learning. Pilot studies should be conducted to evaluate the effectiveness of these automated content adjustments.

Eye tracking alone might not capture certain aspects of the learner's experience. For instance, when visual elements such as text and images are present, students may look at both, but the description might not be clear enough to convey the intended message, leading into confusion. Therefore, in addition to eye tracking, it's essential to consider the environment in which the learning takes place. Mapping cognitive states to the learner's experience remains a significant challenge. Accurately linking cognitive data to the learner's experience requires advanced models that can account for individual differences. Without context, relying solely on neurophysiological data could lead to erroneous conclusions about students' abilities or emotional states, ultimately undermining the effectiveness of adaptive learning systems.

2.7.5 Ethical Considerations

There are several ethical considerations when using neurophysiological approaches, such as eye-tracking, in online learning platforms. One key concern is the storage and management of sensitive data, including students' cognitive states, behaviors, and emotions. It is crucial to ensure that eye-tracking data is securely stored and anonymized to protect student privacy. Students must give informed consent, and there should be clear communication about how their data will be used. Another risk is that algorithms interpreting cognitive states could be biased or inaccurate. Research should focus on ensuring that these tools are validated across diverse student populations to prevent discrimination or misinterpretation. Given the complexities of cognitive states, the algorithms must be continually refined to ensure accurate real-time analysis.

2.8 Neurophysiological Feedback for Trust-Driven Adaptive Explainability in Human-Machine Teaming

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2.8.1 Problem

As AI-driven systems become increasingly embedded in high-stakes and dynamic human-machine teaming (HMT), ensuring trust and performance in these teams remains a critical challenge. Trust is broadly defined as the willingness to rely on another party based on the subjective belief of their reliable behavior under risk and uncertainty [Cho et al., 2015]. In most HMTs, especially in high-stakes and ad hoc teams, swift trust, a temporary and rapidly built trust, is more applicable than traditional interpersonal trust due to the lack of prolonged interactions [Patel et al., 2022]. While human teammates can understand each other through implicit cues, current interactive AI systems lack effective real-time feedback mechanisms to gauge human cognitive states, leading to inefficiencies in decision-making and reduced operator trust. This underscores the need for implicit feedback from human teammates, especially when explicit feedback is limited in high-stakes scenarios.

Neurophysiological signals, including electroencephalography (EEG) and electrocardiogram (ECG), combined with behavioral data such as gaze tracking and action logs, present an opportunity to dynamically assess cognitive load, and stress that support trust assessment [Akash et al., 2018; Choo and Nam, 2022; Hu et al., 2024; Hulle et al., 2024; Shin, 2021; Soni et al., 2021; McGuire and Moshfeghi, 2023; Kingphai and Moshfeghi, 2025]. These signals provide AI systems with a means to interpret the emotional and cognitive states of humans, improving collaborative interactions by understanding implicit human feedback. Explainability has been increasingly recognized as a crucial factor in trust within these teaming paradigms, as it enhances the transparency of machine decision-making [Shin, 2021]. However, static explanations provided by AI lack the ability to respond to implicit feedback from humans. Further, in high-stakes HMT, decision tree-based explanations are inefficient and dynamic natural language-based explanations (e.g., LLMs) are required. Therefore, explanations should be tailored to individual differences, such as distinguishing between novice and expert users, to prevent cognitive overload. Despite this, adaptive explainability is underexplored in dynamic human-machine teams and there is a need to formalize explainability features such as timing, granularity, duration that can adapt based on human's implicit feedback.

2.8.2 Goal

Addressing this gap requires researchers to develop neuroadaptive AI systems that leverage multimodal physiological data to provide adapted explanations, thereby enhancing transparency, reliability, and user experience in high-stakes decision-making scenarios. In that, we aim to understand the correlations between adaptive explainability features and swift trust in dynamic HMTs by leveraging physiological signals as implicit feedback.

2.8.3 State of the Art

The use of multimodal physiological and behavioral data is increasing in recent trust formation and calibration studies. For instance, Choo and Nam [2022] and Hu et al. [2024] incorporated ECG, EEG, and eye-tracking data to measure trust and develop calibration mechanisms using neural networks and CNN models. Other studies on human-machine teaming have proposed various methods to generate explanations based on user models. For instance, Soni et al. [2021] proposed reinforcement learning (RL) and partially observable Markov decision process (POMDP)-based models that rely on pre-processed user types, which may not be applicable in ad-hoc teaming tasks. Earlier approaches, such as model reconciliation [Floyd and Aha, 2016; Sreedharan et al., 2018] and trust-guided behavior adjustments, lacked dynamic real-time adaptability and the ability to incorporate implicit feedback. Recent advancements in large language models (LLMs) present strong alignment with these challenges due to their integrated reasoning capabilities, which enable deeper connections with human interaction than traditional explanatory methods, such as decision trees. For example, ProAgent by Zhang et al. [2024] introduces a novel approach where LLMs proactively adapt their behavior based on the observed environment.

2.8.4 Next Steps

To enable trust-driven adaptive explainability in AI, we propose a conceptual model that leverages neurophysiological signals as implicit feedback to adapt explainability features, including timing (proactive, reactive), granularity (high-level, detailed), and duration (length), to cater to human teammates' emotional and cognitive demands. The adaptations rely on conceptualized correlations between features and user state as a knowledge base integrated into LLM reasoning model. The objectives of the adaptations are to enhance swift trust and team performance in HMTs by reducing the effects of cognitive load and stress that hinder collaboration. In our future work, we plan to validate the proposed conceptual model for swift trust with adaptive explainability using Overcooked AI [Carroll et al., 2019] as a testbed. The rapid data processing capabilities of AI, coupled with the creativity and ethical perspectives of humans, are encouraging human-machine collaboration, particularly in high-stakes operations such as defence and medical operations, where purely human-human or machine-only teams may not be optimal. To advance adaptive explainability in HMT, the research community should refine methodologies for real-time neurophysiological feedback integration, create models capable of mapping physiological responses to trust metrics, and develop standardized datasets for reproducibility.

2.8.5 Ethical Considerations

Advances in BCI's and IIR can facilitate real-time adaptation in AI explanations, fostering improved human-AI collaboration. Additionally, wearable sensors will continue to advance, becoming more generalized and accurate, further enhancing the practicality of neurophysiological monitoring. Ethical considerations, such as privacy, data security, and informed consent, must be central to these developments to ensure the responsible and unbiased deployment of such systems. These systems should remain non-intrusive, prioritizing user comfort and transparency. By bridging neurophysiological feedback with explainable AI, we can enable trust calibration and performance optimization in mission-critical environments, ultimately enhancing decision-making and teamwork in AI-augmented operations.

2.9 Skinner's Black Box: Computational Approaches to Adaptive User behavior Under Cognitive Constraints

Fletcher Scott, RMIT University, Australia

2.9.1 Problem

In online search, goal-directed decision-making about information involves identifying strategies to fulfill a specific information need, assessing the relevance and credibility of the information encountered, and refining subsequent strategies based on what was learned. Yet, research consistently shows that when the information streams in which people must facilitate their goals are fast, dense, and unpredictable such processes will be strained Cabral-Passos et al. [2024]; Hernández et al. [2024]. This pressure is known as task demand Nau et al. [2024]. When such demands are high, people prioritize speed over accuracy Dorfman and Gershman [2019], linked with biased assimilation, or a tendency to interpret new information in a manner that confirms existing beliefs Pilgrim et al. [2024].

A central gap in the literature seeking to understand these processes relates to how task demands alter the brains inferential architecture, shifting the processes responsible for evidence accumulation and tracking of uncertainty in ways that ultimately shape opinion formation and entrench viewpoints. This is despite growing awareness of the role of task demands in the believability of misinformation Mattis et al. [2024]; Törnberg [2022], as well as its role in affective polarization, referring to a dynamic of political conflict where people engage in biased reasoning and become more emotionally attached to their views Iyengar et al. [2019].

2.9.2 Goal

The objective is to determine how specific task demands in online search produce identifiable neural signatures, and how those signatures shape belief updating. Achieving that link will enable the design of adaptive systems that recognize when task aspects distort goal-directed behavior, by overloading capacity or nudging users toward speed over accuracy in their decision-making.

Reaching this goal involves a methodological problem. First, the task demands imposed by such aspects as the page layout, ranking volatility, time pressure and sentiment consistency are latent and can only be manipulated indirectly. Moreover, their neural correlates are confounded by transient mood and arousal shifts Thornton and Tamir [2024], and they cannot themselves be controlled.

We therefore propose a dual research programme: (i) design experiments that systematically co-vary interface components, so that composite task demand can be estimated from the joint pattern of behavioral choices and neural signatures; and (ii) fit hierarchical Bayesian or reinforcement-learning models to users' clickstreams and neural traces, treating behavior as data that invert the generative model each user builds for the task. By recovering the priors, learning rates, and uncertainty estimates that best explain such data, we can ask whether the same parameter set generalizes across interfaces, populations, and modalities (EEG, fMRI, pupillometry). This links task-driven neural signatures to the computations presumed to generate them and provides a protocol for yielding real-time markers that adaptive systems can monitor to support more resilient information seeking.

2.9.3 State of the Art

Beyond traditional statistics, drift-diffusion models (DDMs) are tools for analyzing rapid decisions in the lab. DDMs break each choice into a model of evidence-accumulation rate, decision threshold, and non-decision time, letting researchers test to a higher resolution how a task cue changes behavior Myers et al. [2022]. A growing literature now links these parameters to brain activity measured with EEG, MEG, fMRI, and even single-unit recordings [Gupta et al., 2022]. For example, in value-based decision tasks, drift diffusion modeling has revealed that ex-smokers are more cautious about tobacco-related cues than current daily smokers [Copeland et al., 2023]. In gambling disorder, reduced decision thresholds identified through DDM have been linked to riskier choices and more active gambling behavior [Peters and D'Esposito, 2020].

The limitation is that DDMs focus on moment-to-moment choices and do not model the generative beliefs that users construct while sampling an environment over time. Computational-psychiatry addresses this by fitting hierarchical Bayesian or reinforcement-learning (RL) models to sequences of choices and learning curves, interpreting behavior as the result of predictions and errors that drive belief updates Piray and Daw [2024]; Wilkinson et al. [2023]. Such models have shown, for instance, that overly precise priors can trap psychosis patients in delusions Katthagen et al. [2022], while valence-biased learning rates underpin depressive states Gibbs-Dean et al. [2023]. Critically, when these models are combined with time-resolved physiology—mid-frontal theta, pupil dilation, or dopaminergic BOLD signals, distinct latent variables (uncertainty, volatility, expected value) map onto distinct neural signatures Sherman and Turk-Browne [2020]. This suggests that inverting a user's generative model may serve as a method to identify robust, reusable brain markers of task demand.

2.9.4 Next Steps

The approach is to fit hierarchical Bayesian or RL models to user's clickstream, dwell times, eye movements, and neural data (EEG, fMRI, pupillometry). This procedure recovers individual priors, learning rates, volatility estimates, and evidence-accumulation parameters (i.e., the internal generative model the task induces). We will then ask whether the same parameter set (a) generalizes across different interface configurations and demographic groups, and (b) consistently aligns with stable neural markers such as mid-frontal theta bursts for surprise Mas-Herrero and Marco-Pallarés [2014] or pupil dilation for uncertainty Urai et al. [2017].

By tying latent computational states to reproducible neural signatures, the project delivers a methodology for; (i) a mechanistic approach to interface designs (e.g., does increasing ranking volatility actually raise inferred volatility sensitivity and its frontal-theta correlate?) and (ii) real-time biomarkers that neuro-physiological sensors could feed to adaptive systems. Such may enable search engines or recommender platforms to sense the task conditions when biased updating is likely to occur and deliver explanations or slowing of the interface.

2.9.5 Ethical Considerations

Although these approaches aim to improve user experience, they raise ethical concerns about collecting and managing learner data, especially when recommender systems are allowed to infer users' biases and emotional states.

2.10 What Should We Teach in Neurophysiological Interactive Information Retrieval?

Damiano Spina, RMIT University, Australia

2.10.1 Problem

Wearable devices with sensors are becoming increasingly common. For instance, EEG-equipped earbuds capable of "reading" our brain activity are becoming available at an affordable price, such as the Emotiv MN8, a 2-channel EEG headset that costs under $400.

This technology is making neurophysiological data significantly more accessible to researchers, including those in interactive information retrieval (IIR). However, access to equipment alone is insufficient for conducting effective neurophysiological IIR research. Data collection and analysis present numerous methodological challenges, particularly for students and early-career researchers. Although interest in this field is growing, we lack standardized, easy-to-follow guidelines to help researchers apply correct and sound methodologies.

2.10.2 Goal

We are ready to begin conceptualizing and developing the "Handbook for Neurophysiological IIR", a training and educational resource for researchers interested in using wearable devices to collect neural and physiological sensor data. These include electroencephalogram (EEG), functional near-infrared spectroscopy (fNIRS), electrodermal activity (EDA), and galvanic skin response (GSR), among others. The handbook aims to address complex IR challenges such as characterizing cognitive aspects of information-seeking processes, providing complementary signals for implicit feedback, and advancing Brain-Computing Interaction (BCI). Our focus should be on making experimental methodologies as reusable as possible, documenting pitfalls and lessons learned, building publicly available test collections and benchmarks via evaluation campaigns, and developing comprehensive teaching resources and curricula tailored to neurophysiological IIR.

2.10.3 State of the Art

There are a number of resources that have been fundamental in training and guiding researchers in the field of IIR. Just to name a few, the book by Kelly [2007] on "Methods for Evaluating Interactive Information Retrieval Systems with Users" is a must-read for any researcher interested in conducting lab user studies in IIR [Kelly, 2007]. Similarly, the book by Sakai [2018] is an excellent reference to the use of power analysis and statistically significance tests in IR. To my knowledge, no equivalent resource exists for neurophysiological IIR experimentation. In the field of IR, there has been recent advancement in developing training and educational resources – e.g., see [Bauer et al., 2023; Markov and de Rijke, 2019; Spina et al., 2024; Spina, 2025] – and there are new books that cover advances topics and techniques in our area [Alonso and Baeza-Yates, 2024], including Generative AI [White and Shah, 2025]. However, the intersection between IIR, cognitive and neural sciences, and wearable devices remains largely unexplored.

2.10.4 Next Steps

I can think of three immediate steps that we could take as a community:

Enhancing re-use of neurophysiological IIR experimentation. A starting point could be reflecting on our own practices and see to what extent we adhere to the principles to support re-use in IIR and the Five Levels of IIR Resource Re-Use proposed by Gäde et al. [2021]. How many of these levels are being covered already in the existing literature on neurophysiological IIR?

Characterizing pitfalls in neurophysiological IIR. Another pragmatic step could be working collectively towards a number of common mistakes or pitfalls that are likely to occur in neurophysiological IIR experimentation ("I've been there, make sure you do X and not Y!"). One of my favorite examples is the paper by Crook et al. [2009] on online experimentation.

Building publicly available datasets and evaluation campaigns. Finally, developing reusable datasets and benchmarks that are publicly available. A very effective way to accomplish this is by setting up evaluation campaigns: what a TREC Track, CLEF Lab, or NTCIR Task on Neurophysiological IIR would look like?

By advancing in these directions, I believe we will be well-prepared to create the "Handbook for Neurophysiological IIR."

2.10.5 Ethical Considerations

Given the sensitivity of neurophysiological data collected through wearable devices, issues of data privacy, informed consent, and the potential for bias in data processing are critical. Researchers should be trained and guided to address these ethical challenges responsibly and transparently.

2.11 Neural Signatures of Query Variations: A Neurophysiological Investigation of User Responses to Varying Query Formulation in Search System

Shuoqi Sun, RMIT University, Australia

2.11.1 Problem

Information retrieval research faces a critical disconnect between algorithmic evaluation metrics and authentic user experiences. Studies show substantial variation in how users construct queries across different search contexts [Alaofi et al., 2022], yet current frameworks prioritize algorithmic relevance over human cognitive processing. We lack understanding of how different query formulations affect information processing from both neurophysiological and subjective perspectives. Despite their potential for providing objective measurement of cognitive processes [Ji et al., 2024a; Kirwan et al., 2023; Moshfeghi et al., 2013], tools like EEG and eye-tracking remain underutilized in query formulation research [He et al., 2025]. This knowledge gap is particularly urgent as LLMs increasingly become primary interfaces for global information access [Edson de Carvalho Souza, 2025; Bieniek et al., 2024], where despite advances in prompting techniques [Zhuang et al., 2024a,b; Sun et al., 2025], we minimally understand how varying query structures affect users' ability to process returned information. Understanding neural signatures of query variations has become essential for developing human-centered search systems that align with users' cognitive processes and information examination behaviors.

2.11.2 Goal

The research community should develop a neurophysiologically-informed framework for evaluating query variations in search systems through four strategic objectives:

First, establish standardized protocols for measuring neural signatures across varying query formulations. This requires integrating EEG, eye-tracking, and physiological responses to comprehensively assess cognitive load and information processing efficiency during search interactions. Second, bridge neurophysiological data with subjective user experiences through holistic evaluation metrics. By correlating neural patterns with subjective reports, researchers can create evaluation frameworks that authentically reflect users' cognitive experiences. Third, investigate how different query formulations affect diverse user populations based on domain expertise, search literacy, and cognitive abilities, etc. This would enable the development of adaptive search interfaces that accommodate varying query capabilities across different user groups. Finally, transform these insights into actionable design recommendations, including interfaces and retrieval models optimized for cognitive efficiency rather than merely maximizing traditional relevance metrics.

These objectives would advance our understanding of how query formulation shapes the cognitive dimensions of search experiences, prioritizing human-centered approaches grounded in neurophysiological evidence of information processing.

2.11.3 State of the Art

Recent advancements in information retrieval increasingly leverage neurophysiological tools [Jacucci et al., 2019; Gwizdka and Mostafa, 2016; Paisalnan et al., 2021b] to study user cognitive processes during search interactions. Ji et al. [2024a] employed physiological measures to characterize cognitive states across search stages, revealing higher cognitive loads during Query Submission and increased engagement during Relevance Judgment. Kirwan et al. [2023] advocate for integrating neurophysiological and behavioral methods to assess cognitive processes across different search interface interactions. Gwizdka [2018] demonstrated that pupillometry and single-channel EEG can effectively infer web page relevance, while Pinkosova et al. [2020] examined the temporal nature of when relevance judgments physically manifest using EEG. Further work by Pinkosova et al. [2022] identified distinct ERP components during relevance assessment, including early P100 components associated with selective attention, suggesting relevance detection begins earlier in cognitive processing than previously understood. Moreover, Scharinger et al. [2020] explored mental processing demands during text-picture integration using EEG and eye-tracking. Despite these advances, studies directly investigating neural responses to varying query formulations in search systems remain scarce. This gap becomes increasingly critical as search interfaces evolve. Existing literature provides methodological foundations but lacks direct application to query variation contexts.

2.11.4 Next Steps

To advance this research direction, the community should consider several strategic approaches:

First, standardizing neurophysiological measurement protocols for search evaluation. Researchers need to establish consensus on which EEG metrics and eye-tracking measures best capture cognitive load across varying query formulations. This standardization would facilitate cross-study comparisons and accelerate knowledge accumulation.

Second, developing systematic experimental designs that manipulate query formulation while controlling for confounding variables. Query variations could be structured through predefined templates, with participants encountering results corresponding to each formulation type.

Third, implementing inclusive research practices through robust sampling strategies that reflect diverse user populations. Studies should include participants across different expertise levels, literacy backgrounds, and cognitive abilities to understand how neurophysiological responses to query variations differ across demographic factors.

Fourth, establishing ethical frameworks that balance rigorous measurement with participant privacy and well-being. As we collect sensitive neurophysiological data, ensuring appropriate consent and data protection becomes paramount.

Fifth, creating holistic evaluation metrics that bridge objective neurophysiological data with subjective user experiences. These metrics should authentically reflect actual cognitive experiences rather than relying solely on algorithmic performance indicators.

The collective goal should be identifying neural signatures associated with varying query formulations and translating these insights into human-centered search interfaces that optimize for cognitive efficiency and user satisfaction.

2.11.5 Ethical Considerations

Neurophysiological research on query variations raises critical ethical considerations. Brain activity data requires robust privacy protections with strict data minimization principles. Participant well-being demands careful session design and appropriate task selection. Inclusive recruitment is essential while acknowledging demographic variations in neurophysiological responses. Finally, researchers must avoid deterministic claims about "optimal" query structures based solely on physiological data, instead balancing measurement with respect for diverse search experiences.

2.12 Is Context All You Need? The Case for Personalized Information Behavior Sensing and Understanding in the Wild

Flora D. Salim, University of New South Wales, Australia

2.12.1 Problem

Understanding information behavior is crucial in everyday, real-world contexts – like how people search, use, and share information, and inform their planning and decision-making processes. Understanding information needs is one of the holy grails of cognitive science, ubiquitous computing, IR, and recommender systems research. On an individual level, awareness of one's own information behavior can greatly impact personal productivity and wellbeing. User information behavior also influences product uptake, stimulates market demand, and ultimately determines the success or failure of digital products and services.

We live in an age of potential information overload – with constant emails, notifications, news updates, and endless content streams vying for our attention. How we manage and respond to this onslaught of information is a complex behavior pattern that we can uncover, examine and improve.

However, modeling the information behavior is an utterly complex and multifaceted beast of task. It consists of understanding fine-grained physiological, cognitive, emotional, and behavioral states and routines. The downstream tasks and applications for this model are many and varied, including cognitive load sensing, attention management, stress management, just-in-time recommendation system, personalized digital assistance, chatbot agents, and many more.

With the promise of myriads of off-the-shelf wearable sensors available to researchers, can we truly discover user information needs and behaviors in daily life using multimodal sensing, particularly with easy-to-use off-the-shelf sensors we are all used to wearing by now – wristworn wearables or watches, earables, rings, and even cognitive sensing headbands?

2.12.2 Goal

Given a series of multimodal sensor channels as input, associated with individual users, generate prediction of the target information behaviors and stages (e.g., information seeking, information processing, information sharing), or the applied downstream applications.

The goals are:

- To decipher context signals to determine user needs and their respective information behavior stages.
- To model and predict context-aware information behavior regardless of data availability / unavailability and signal quality.
- To discover personalized information behavior profiles, useful for developing personalized digital assistance.

2.12.3 State of the Art

Despite the years of research on multimodal, neurological / cognitive, and physiological sensing to determine user information behavior and needs, most of the user studies and data collection have only been done in the lab and were limited to just the very first steps of information processing (e.g., translating cognitive states of reading activities – captured by fNIRS and/or EEG caps – to textual transcription, or in another word – from thoughts, captured with EEG signals, to text –word by word), e.g. [Hollenstein et al., 2020; Duan et al., 2023; Wang et al., 2024].

Research on understanding information needs and behaviors in the wild have been done largely with contextual spatio-temporal signals derived from inertial, physiological, and environmental sensors typically available from mobile sensing and/or wearables or with off-the-shelf environmental sensors, with the goal for assisting users interacting and/or searching for information while they are on the move (e.g. commuting, traveling, or shopping) [Kang et al., 2022; Ren et al., 2018; Moshfeghi and McGuire, 2025], determining apps they will need or use in certain contexts or tasks [Khaokaew et al., 2021, 2024b, 2022], uncovering the types of information needed for the daily tasks of information workers [Khaokaew et al., 2024a; Liono et al., 2020; Trippas et al., 2019], understanding user cognitive and emotional engagement in classroom learnings [Gao et al., 2020, 2022], the understanding & prediction of information needs under Q/A scenarios [Moshfeghi and Pollick, 2019; McGuire and Moshfeghi, 2024; Michalkova et al., 2022; Moshfeghi et al., 2019], the ability to retrieve relevant passage entirely from a neurophysiological query input [McGuire and Moshfeghi, 2025], and for attention and interruptability management [Anderson et al., 2023]. However, to date, this approach which relies heavily on physiological and inertial sensors from mobile and wearable provides a high-level abstraction of states of information behavior. Recent work on information behavior sensing managed to detect the stages of information seeking processes [Ji et al., 2024a], using EEG, eye-tracker, wristworn wearables and earables to detect both cognitive and physiological signals. However, this method will not work outdoors, outside the lab, as it is heavily dependent on the eye-tracker signals. Self-supervised learning (SSL) provides a promise for general models capable for domain adaptation for multiple domain-specific datasets and downstream tasks [Deldari et al., 2022]. For example, SSL has been applied on EEG representation learning on a wider variety of tasks (e.g. driver distraction monitoring [Mohammadi Foumani et al., 2024]). Generalization across users can be made more robust even if there are missing sensor channels in pretraining, finetuning, or inference stages [Deldari et al., 2024]. LLMs can be used to supplement contextual and semantic information if they are sparse and/or missing [Khaokaew et al., 2024b]. Framing the representation as context-dependent helps multimodal sensing research for personalized information behavior understanding to be more targeted and selective in data collection, modeling, domain adaptation, and reasoning. Context-aware models provide the needed abstraction for user behaviors and its interaction with the environment, and context-aware systems provide relevant information to the users, with relevancy to be dependent on the user's task [Abowd et al., 1999]. As such, context, indeed, is (almost) all you need for understanding information behavior from mobile and wearables sensors. However, to truly understand one's information behaviors in various contexts, a higher resolution, fine-grained abstraction of contexts in relation to information behavior is needed to model and reason about the cognitive and behavioral signals across many tasks and environments.

2.12.4 Next Steps

There are several open-ended questions:

- Can we detect what information do users really need in the wild at any given context?
- Does understanding information behavior require detection of what user has in mind? Do we really need to uncover what user thinks – word by word? Or do we need to just detect conceptual abstraction of what user has in mind?
- How to determine which signals really matter to the end goals in mind?
- What resolutions of sensing and detection are required and for what tasks? Is the choice on the resolution context and task dependent?
- Given the high non-compliance of wearable usage in daily activities, how does information behavior sensing with just off-the-shelf wearables can succeed beyond the lab?
- If we are to build a general model for information behavior sensing across many downstream tasks, what are the guidelines on responsible sensing and modeling?

2.12.5 Ethical Considerations

- How much data do we need to model information behavior in the wild? Saying 'as much as we can get' does not cut it. The era of brute force sensing and modeling is over. Hence why newer abstraction of context is needed also to ensure responsible data access and privacy.
- The end users need to have the right to have their data and models forgotten. Machine unlearning should be a goal of such a responsible behavior sensing system.

3 Discussion

Following the discussion of individual statements presented during the workshop, an open discussion was held among all participants. This dialogue led to the identification of key research priorities for the field, as well as a set of open research questions that can guide and shape future work.

3.1 Key Areas of Research

Terminology. There was an extensive discussion on highlighting the importance of the terminology and key concepts and constructs within this research area, which stands at the intersection of multiple disciplines. We discussed the need to create a comprehensive glossary to help ground researchers with common interests in neurophysiological IR, bringing together diverse backgrounds and expertise.

Bandwidth. The discussion also highlighted the limited but complementary bandwidth of current neurophysiological interaction technologies, such as eye-tracking, gestures, and brain-computer interfaces (BCIs), and how their application in academic research often differs from industry practices. While these signals offer valuable, but sometimes narrowly scoped data, into user state, it may be that the broader input spectrum including several modalities remains underutilized. Participants emphasized the need to advance not only our understanding of user behavior through these modalities, but also system-side approaches that integrate them more effectively in human-computer interaction loops. This includes combining multiple physiological signals to compensate for limitations of individual signal modalities and fusing them with existing interaction modalities (e.g., speech, touch, visual context) to create more robust, adaptive, and context-aware systems. Such integrative strategies are essential for fully realizing the potential of neurophysiological data in interactive technologies, including IIR.

Modalities and Devices. The wide range of devices and physiological data modalities was a key point of discussion. Participants noted that different modalities, such as EEG, eye-tracking, skin conductance, and gesture recognition, carry distinct types of information, follow different levels of adoption in practical devices, and vary widely in terms of usability and reliability. Some signals are highly sensitive to artifacts, limiting their applicability in real-world settings, while others may suffer from latency or low temporal resolution, affecting their suitability for timely interaction. Modalities can be unidirectional (serving as either input or output) or bidirectional, particularly in closed-loop systems. The invasiveness of devices, ranging from minimal-contact wearable to more intrusive sensors, also influences user acceptance and deployment potential.

Stimuli Modeling. The workshop addressed the value of expanding multimodal learning to include not only physiological signals but also the modeling of stimuli and behavioral responses. It was emphasized that jointly analyzing task context, presented stimuli, and user reactions can lead to a more comprehensive understanding of user–system interaction and complement the limited cognitive and affective information that is available from the physiological sensors. This integrated perspective supports the identification of meaningful associations between digital information humans perceive and behavioral or physiological patterns. Incorporating both external stimuli and internal responses may improve the accuracy and interpretability of models, contributing to the development of more effective and context-aware IIR.

Experimental Methodology. There is a consensus on the need for more systematic approaches to guide the design and execution of experiments in this area. In particular, participants emphasized the importance of explicitly addressing ecological validity and the trade-offs between conducting studies in controlled versus naturalistic environments. Providing shared protocols and more detailed descriptions of experimental settings would improve transparency and enhance the reproducibility of signal preprocessing and measurement methodologies.

Ethical Considerations. As also evidenced by the reflections provided in the statements, participants acknowledged the efforts needed with regard to research integrity and ethics in this area. In particular, data privacy and governance, bias and fairness (e.g., personalization), and responsibility and reliability in the way the research is conducted and disseminated.

3.2 Research Questions for Future Work

In addition to the open problems identified in the statements analyzed during the workshop, the discussion led to the identification of a non-exhaustive list of research questions to guide future directions in this area.

- What does a glossary (defining constructs, instruments, measures, signals, etc.) of neurophysiological IIR look like?
- What are the key challenges and barriers to successful academia-industry collaboration in advancing neurophysiological IIR research, and how can they be overcome?
- What are the limits in terms of characterizing user-system interaction with neurophysiological signals and devices (e.g., eye-tracking, wearables, gestures, BCI)?
- What is the range of experimental methodologies that are being used in neurophysiological IIR? What is the ecological validity of such settings?
- How can we make resources more accessible to other researchers? Which approaches should we take to make our experiments more reproducible, ensure validity of research findings and data, make our data and resources more reusable?

- How can research integrity and ethics be improved in this area? What measures can be taken to enhance responsibility and reliability in the conduct and dissemination of research?

4 Conclusion

The International Workshop on NeuroPhysiological Approaches for Interactive Information Retrieval at CHIIR'25 (NeuroPhysIIR'25) had 19 participants and discussed 12 statements. We believe the workshop successfully achieved the goals that we targeted. In particular, we enhanced the awareness and adoption of neurophysiological methods among the broader IIR community; we came up with a roadmap for addressing key methodological challenges in applying neurophysiological methods to IIR research, and we identified key research questions in the field. We also created a Discord channel that aims to bring together researchers and practitioners interested in neurophysiological IR research.[3]

The fruitful discussion and the wide spectrum of open challenges identified during the workshop demonstrate a positive outlook with significant opportunities for further development. More initiatives like this workshop are needed to foster the community and advance knowledge in neurophysiological approaches for interactive information retrieval.

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