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Understanding Feeling-of-Knowing in Information Search: An EEG Study

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The realisation and the variability of information needs (IN) with respect to a searcher's gap in knowledge is driven by the perceived Anomalous State of Knowledge (ASK). The concept of Feeling-of-Knowing (FOK), as the introspective feeling of knowledge awareness, shares the characteristics of an ASK state. From an IR perspective, FOK as a premise to trigger IN is unexplored. Motivated by the neuroimaging studies in IR, we investigate the neurophysiological drivers associated with FOK, to provide evidence validating FOK as a distinctive state in IN realisation. We employ Electroencephalography to capture the brain activity of 24 healthy participants performing a textual Question Answering IR scenario. We analyse the evoked neural patterns corresponding to three states of knowledge: i.e. (1)“I know”, (2)“FOK”, (3)“I do not know”. Our findings show the distinct neurophysiological signatures (N1, P2, N400, P6) in response to information segments processed in the context of our three levels. They further reveal that the brain manifestation associated with “FOK” does not significantly differ from the ones associated with “I do not know”, indicating their association with recognition of a gap in knowledge and as such could further inform the IN formation on different levels of knowing.

Categories and Subject Descriptors: H.3.3 [**Information retrieval**]: Users and interactive retrieval

General Terms: Performance, Experimentation

Additional Key Words and Phrases: Information Need, Information Retrieval, Anomalous State of Knowledge, IR, Metamemory, Metacognition, Feeling-of-Knowing, EEG, ERP

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1. INTRODUCTION

A search process is initiated as a result of a realisation of Information Need (IN) [Cooper 1971]. According to the cognitive outlook in Information Seeking & Retrieval (IS&R) literature, the searcher is depicted as a cognisant entity in the IR process and so is the main entity influencing the character of IN [Taylor 1962, 1968; Belkin et al. 1982a; Kuhlthau 1991; Ingwersen 1984, 1996; Ingwersen and Järvelin 2005; Saracevic 1997]. The insight into internal processing behind the IN realisation remains hypothesised and generally described according to frameworks such as Minsky's Frame Theory

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[Minsky 1974] adapted by Cole [Cole 2012]. Still, one of the most respectable additions to IN concept remains Belkin et al.'s Anomalous State of Knowledge (ASK) [Belkin et al. 1982a,b]. It delineates the nature of IN from the angle of the users' cognitive context [Ingwersen and Järvelin 2005].

Holistically, it is known as the cognitive context of the user [Ingwersen and Järvelin 2005] that describes the user's (knowledge) readiness in a given situation. For instance, the user's topical knowledge, the amount of knowledge the user knows about a given topic, mentioned by Kuhlthau [Kuhlthau 1991] as the means of assessing the user's awareness of how to define IN. The employed cognitive abilities are in focus since they are vital in updating users' awareness and understanding of their state of knowledge in a given scenario. The premise of ASK is clear. With respect to the stimuli (e.g., a problematic situation) the user faces, their state of knowledge is anomalous, i.e. insufficient to solve this situation. Belkin et al. [Belkin et al. 1982b] further hypothesised that the variants of ASK are associated with different anomalies. These are believed to exist depending on the levels of the individual's knowledge with a problem statement as a reference guide to the anomaly. Further specification of ASK variants, especially in the area of how to distinguish them, remains, however, a question. Belkin and Kwaśnik [Belkin and Kwasnik 1986] expanded on the classification of the ASK using the structural characteristics of problem statements. Later, Wissbrock [Wissbrock 2004] defined two sides of an anomaly: 1) cognitive and 2) linguistic. Taking aside point (2), which deals with an articulation aspect of the IN in terms of the natural language, the focus on the user's cognitive side seems to offer a guide to define the variants.

Early works by Taylor [Taylor 1962] conceptualising IN already contain signatures of engaged cognitive functions and "some internal insight" the user performs. He produced an early depiction of IN as a hierarchical concept with differing levels of internal (e.g., user's recognition, understanding and interpretation of their IN) and external (features of IN, e.g., specificity, articulation) inter-dependent manifestations. This connection explains the character of visceral (in-brain) IN expressions [Taylor 1968] lacking specificity as the user's understanding is limited as it operates with imperfect output from internal information sources. This conforms to the anomaly, which is experienced as a result of recognising insufficient or inconsistent knowledge [Belkin and Kwasnik 1986]. Also, Cole [Cole 2012] explained that as a pre-manifestation of IN, an internal cognitive assessment triggers the user's awareness of a knowledge gap concerning the problematic situation. The orientation to the cognitive underpinning of ASK might prove vital to understanding how and what INs are generated.

Very early notions of the role of metacognition related to ASK were suggested by McAleese [McAleese 1985]. The user's realisation relies on the introspective processes of metacognition [Dunlosky and Metcalfe 2009]. Metacognitive processes are vital human introspective abilities that pass the information received from engaged internal components to evoke the most accurate representation of the present state of the user. Metacognition encompasses processes of auto-consciousness and self-awareness demonstrated in thinking, learning, knowing and experiencing [Metcalfe 2009]. The availability of internal information (knowledge) is essential for the user to learn in the context of ASK. This idea brings us to emphasise a specific part of metacognition, metamemory [Nelson 1990]. In particular, it implies that we are able to introspect on memory processes able to use certain cues to assess the quality of knowledge [Thomas et al. 2016]. It is known to engage memory control and monitoring, making judgments about the strength of one's memories and providing, thus, the answer to the question "Do I think I have the knowledge?", emphasising one's thinking process to evaluate their (anomaly of) state of knowledge. In line with this notion is the neuropsychological model of realisation of information need [Moshfeghi and Pollick 2019] by Moshfeghi and Pollick. Their exploration of the realisation of INs found traces of active brain regions commonly associated with studies of metamemory and, in particular, highlighted similarities with the state of Feeling-of-Knowing (FOK) [Robert L. Widner and Smith 1996].

FOK is triggered by the self-aware mechanisms of metacognitive processes reflecting a persons feeling at the time of retrieval about whether they will recognise a missing answer they cannot recall now [Schwartz et al. 2014]. Then, in what relation, can FOK be to ASK? We can establish that FOK, as a state of knowledge in the absence of knowledge [Thomas et al. 2016] meets the essential characteristics of an ASK state, and so, the inaccessibility of information, which may potentially lead to IN. Thus, if the metamemory is the fundamental mechanism in this scenario, our goal is laid out, as to methodologically study the metamemory in the context of ASK's origin with a focus to understand the state of FOK.

The research into metamemory assessment often employs the Graded Recall approach [Maril et al. 2003]. This method uses the graded nature of the participants' memory recall and its outcomes as the means to explain different states of knowledge, for instance, FOK as a separate entity on the recall spectrum [Maril et al. 2005]. This idea leads to our speculation that ASK variations could be manifested based on the different specificity of recall outcomes. In this context, FOK represents an intermediate recall state on the Graded Recall spectrum [Maril et al. 2005, 2003]. From the perspective of ASK, the anomaly in the knowledge the user realised takes the form of FOK the user acknowledged. Accordingly, the FOK appears to be a particular state of ASK, i.e. an ASK variant [Belkin et al. 1982b]. To summarise, the application of the Graded Recall accounts for metamnemonic processes embedded in the process of knowledge awareness [Maril et al. 2005] and, thus, represents the character of ASK as graded with anomalies as a product of Graded Recall. As a result, depending on the variants of anomalies, the final ASK is modified, particularly looking at the FOK state as a proposition of the ASK variant.

Despite FOK being supported by extensive theoretical [Hart 1965; Thomas et al. 2016] and user-based knowledge [Irak et al. 2019a; Norman et al. 2016a; Risko et al. 2016; Isingrini et al. 2016], FOK has little promotion in IR-based research. Furthermore, aiming to investigate organic metacognitive processes behind FOK, the application of regular IR techniques (e.g., interviews, questionnaires [Kuhlthau 1991]) of user-behavioural research is limited in capturing the drivers of IN realisation and potentially leading the user to information overload. Motivated by an increasing output of *NeuraSearch* research [Moshfeghi 2021] which employs neuroimaging techniques to capture searchers' underlying neural mechanisms activated during an IR task (e.g., relevance [Allegretti et al. 2015; Pinkosova et al. 2020], query terms [Kangassalo et al. 2019]), fits with our own aims. Relevant to our aim is the fMRI-data-driven work by Moshfeghi and Pollick [Moshfeghi and Pollick 2019] which drew the neurophysiological correlates of IN realisation that indicated the co-activation of metamemory, particularly patterns commonly found during FOK investigations. The viability of this approach to capture the metacognitive processes is the key feature.

On this basis, we developed a computerised interactive Question-Answering (Q/A) Task where participants responded to a series of general knowledge questions whilst their electrical potentials generated by the brain were monitored using Electroencephalography (EEG). To account for a variety of metamemory awareness outcomes, we used the Graded Recall approach [Maril et al. 2005, 2003] to formulate a set of user-predefined response choices. In addition to the two levels of the recall spectrum, i.e. (1)"I know" (KNOW) and (2)"I do not know" (NKNOW), we expanded on a third level, (3) intermediate recall state accompanied by "I might know" (FOK). We further refer to this set as "Meta levels". In our case, FOK allows for a more accurate specification of the user's state of knowledge by applying FOK's proposition of positive future prospective performance.

Our analysis will focus on the Event-Related Potentials (ERP) that represent brain response to an event (see 3), e.g. stimuli, decisions, responses [Kappenman and Luck 2015]. In our case, the stimuli were the questions given to the participants in the task. By extracting the Event-Related Potentials (ERP) related to such Meta levels, we unfolded the neurocognitive processes that subserve the user's information processing. To this aim, we focused on the following research questions (RQs):

(1) *"Is there a clear, detectable, physical manifestation of FOK in the context of metacognitive states of knowledge (Meta levels)?"*
(2) *"Do the neural manifestations of these three Meta levels differ and how could the differences inform the context of user's ASK in IR?"*

In summary, our study helps to create a bridge between conceptual and behavioural studies by providing new insights on the brain correlates of FOK in the context of the searcher's IN. This study acknowledges a new spectrum of variations in users' awareness of knowledge in an IR scenario and brings more specificity into the quest to answer the "How is the cognitive perception of internal information (knowledge) involved in IN formation and how does it change the expected information outcome?". We discuss our findings of neurophysiological modulations reflecting the cognitive states of knowing, providing instrumental knowledge of variations in the searcher's specificity of IN.

The remainder of the paper is organised as follows: Section 2 presents related literature followed by Section 3 which sets out the preliminaries of the EEG technique and serves as the point of reference for EEG/ERP-related terminology. Next, Section 4 presents at length the experimental methodology. Results are reported in Section 5 and discussed in Section 6. Finally, Section 7 presents our key conclusions and discusses the implications of our study for IR research.

2. RELEVANT WORK

2.1. Information Need Realisation

The stimuli the people encounter at a certain point in time convey information they need to interpret and process using their internal cognitive abilities [Ingwersen 1984, 1996]. Information Need (IN) occurs as a realisation of discourse between the user's sources and capabilities in the moment of a problem situation and the information resolving the situation encoded in the problem itself. This discourse is manifested by the concept of IN [Cole 2012]. Seminal work by Taylor [Taylor 1968] introduced the concept of IN in a graded fashion (Q1-Q4) with searchers moving through consecutive phases of expressiveness to figure out what is their "actual" IN. The within-brain representations of the IN exist in the user's brain, sourced from a cognitive state where the user is not yet able to sufficiently express the need. This early work already recognised IN as a reflexive and dynamic concept conforming to the setting in which it is satisfied, i.e. iterative IR process. Subsequently, Belkin et al.'s [Belkin et al. 1982a] ASK Model referred to the user's information anomaly as the source of this insufficiency that needs to be filled. Kuhlthau [Kuhlthau 1991] analogised both of these theories and concluded that vague INs at initiation are experiential in nature, i.e. they are likely to be connected to the user's existing knowledge. Knowledge is represented as an integral part of the user's conceptual state of the world, the information and beliefs they gathered throughout their lifetime. The research community commonly agree on conceptual models portraying the user's picture of the world, such as Taylor's "State of Readiness" by Mackay [Mackay 1960], Belkin et al.'s "Conceptual State of Knowledge" [Belkin et al. 1982a] or Ingwersen's "World Knowledge" [Ingwersen 1984] as the constructs of the users' storage of information and beliefs. In addition to the representation of IN through the user's knowledge deficiency [Belkin 1980], the ASK Model first hypothesised variants of anomalies and as a consequence, variants of ASK. As a result, ASK is also impacted by the context of the information scenario and the quality of defined information [Belkin et al. 1982b]. Accordingly, five ASK classes were introduced reflecting different information problems. It has become a practice to utilise the user problem statements as the representations of ASK [Belkin and Kwasnik 1986]. Aligned with this research, the study by Yuan et al. [Yuan et al. 2002] expanded each class with the relevancy criteria based on the qualitative analysis of over 150 information problems. The results showed different usage of relevance criteria depending on the type of ASK.

Another side of the anomaly represents the focus on its cognitive aspects [Wissbrock 2004] in order to specify the user's ASK. The cognitive mechanisms orchestrate the understanding of the present state of knowledge in order to figure out what is needed and how new information would alter the current knowledge. Therefore the output of this process supplies the user with cues to guide their response behaviour. A few works speculated about how this exchange is organised [Ingwersen 1984] with a notable book by Cole [Cole 2012] defining the key elements and user's internal functioning supporting this process. Recently, Cole [Cole 2020] revitalised the attention to ASK and, in particular, accentuated its impact as a gateway to discovering users' actual (visceral) INs.

Referring back to Taylor's taxonomy of IN, the searcher's inquiry is underlain by "area of doubt" [Taylor 1968, 1968, p.179]. The term area intuitively implies that the anomaly prevents the user from creating a consistent and complete picture of the world. In addition, this idea offers a broad range of options on how to look at the early manifestations as well modalities of INs, for instance, dissatisfaction, confusion, low confidence [Kuhlthau 1991]. These characteristics conform to the definition of ASK's realisation of anomaly accompanied by hard-to-express feelings. To address this user's cognitive context, we look at the underlying processes producing information about the user's state of knowledge and readiness. In addition, the work carries early support for metacognitive, i.e. self-exploratory mechanisms, that allow the user "to look through his own files" [Taylor 1968, 1968, p.181]) to understand own cognitive context concerning the area of doubt.

2.1.1. ASK and Metamemory. ASK's disposition is hypothesised on a situation when the user cannot specify their needs (in the form of a query to a system) concerning their problematic situation. However, the user is aware and can recognise an anomaly (i.e., a gap) in knowledge related to the problem. ASK then represents a state present with the anomaly as inadequate knowledge to resolve the situation [Belkin et al. 1982a].

The authors also further hypothesised that variants of ASK are associated with different anomalies depending on the level of the individual's knowledge. They illustrated a supportive concept, "Conceptual State of the Knowledge" [Belkin et al. 1982a] which is a user's repository of knowledge, beliefs and past experiences. At any point in time, users can make an inquiry to increase their awareness about their current state of knowledge. Once the anomaly is detected, the state is declared anomalous. From a cognitive viewpoint, the state of knowledge mediates the interactions between humans and between humans (users) and systems. When interacting with the system, the overall aim is for the user to develop a more clear and concise picture of the problem. If documents represent "a coherent state of knowledge" ([Belkin et al. 1982a], 1982, p. 64), a query or a statement related to a problematic situation, as a representation of the anomalous and incoherent state of knowledge, is iterated in a journey towards resolving it. This relates to Belkin et al.'s assumption that for a type of an IR system built upon the recognition of ASK (i.e., ASK-IR [Belkin et al. 1982b]), there exist different types of ASK [Belkin and Kwasnik 1986], which would require different retrieval mechanisms [Belkin et al. 1982b]. Implementation of the ASK-IR system requires a representation of these types of anomalies upon which INs could be specified. Belkin et al. advise on criteria for how to specify ASK derived from the problem statement [Belkin et al. 1982b]. Wissbrock [Wissbrock 2004] delineated two areas to characterise anomaly from user-perspective: 1) cognitive ("How specific the anomaly is to the user?") and 2) linguistic ("Can I create a narrative?"). As part of this paper, we will focus on (1) to support the cognitive notions of ASK variants.

McAleese [McAleese 1985] speculated a link between ASK and metacognition. He presented ASK as "what one does not know", which occurs due to the user's awareness triggered by the application of reflection and perception as the tools of underlying metacognitive mechanisms. In particular, we aim to evaluate the position of FOK in relation to users' INs. We approached this task by investigating if there exists variability in brain responses that can inform us about the early manifestations of the realisation of anomalies in knowledge, in particular the one corresponding to FOK. In summary, metamemory [Nelson 1990] is of particular interest, as its presence as part of cognitive mechanisms, intuitively implies that we are able to introspect on memory processes related to information search, storage, and retrieval. Its unique ability to perform a subconscious assessment of the quality of knowledge [Thomas et al. 2016] evokes its relevancy with respect to the realisation of the anomaly in knowledge.

2.2. FOK and Information Search

The user's feeling of knowing (FOK) reflects the likelihood of eventually recognising information items they cannot currently recall [Schwartz et al. 2014; Hart 1965]. The FOK judgments are a common measure used in numerous experimental scenarios that monitor the function of metamemory, processes of memory search, storage, and retrieval [Chua et al. 2017; Norman et al. 2016b; Schwartz 1994; Dunlosky and Metcalfe 1965]. The metamnemonic control underlying eliciting FOK is a valuable cognitive asset allowing the users to increase their introspective awareness and so indicate their present state of memory [Thomas et al. 2016]. The questions are *"how informative the metacognitive states are"*, *"what their characteristics are"*, and ultimately to learn *"how they affect the user's subsequent cognitive behaviours"*. For example, differences in the strengths of evoked FOK were found to drive different memory searches; where people with stronger FOK spent more time searching for information than those with weaker FOK, some even giving up [Thomas et al. 2016]. Further, works focusing on the content of memory showed that contextual information significantly influences FOK judgments [Brewer et al. 2010]. The contextual information (called non-criterial), such as partial incomplete retrieval can be temporarily seen as relevant for the user to rely on in order to predict the availability of the target information (information in question) [Koriat 1993]. The more detailed retrieved context is, the higher FOKs are induced for the target information [Koriat and Nussinson Levy-Sadot 2001]. Analysis of subsequent user studies highlighted the accurate performance of FOKs, meaning a successful recollection or recognition, as a function of cue familiarity [Isingrini et al. 2016].

Furthermore, the FOK judgments reflect the user's prospective state of knowledge (performance) in the absence of present knowledge [Thomas et al. 2016]. With this notion and demonstrating the FOK as a driver of user-controlled actions and decisions to resolve them [Koriat 2000, 1993], the investigation of FOK as a state of user's incomplete view of the world [Belkin et al. 1982a; Ingwersen 1984], has clear applications within the field of user information- and information search behaviour [Keshavarz

2008]. The prospective position of FOK was strengthened by utilising the user's rates of FOK strengths in relation to Internet search. The focus of studies by Risko et al. [Risko et al. 2016] and Ferguson et al. [Ferguson et al. 2015] was to study a relationship between a user's inner sense of FOK, as an indicator of the internal knowledge, and external information available on the Internet. Access to available external information means for the user to subconsciously rely on this information, extending it as part of their scope of knowledge [Fisher et al. 2015], and so to affect the FOK. FOK implies temporal not-knowing of the information in question, making it a premise of IN. Following on, IN can be seen as a product of our internal knowledge with the sense of availability of external information.

The presence of specific metamnemonic users' online requests resembling the INs was also acknowledged by Arguello et al. [Arguello et al. 2021], naming these Tip-of-Tongue (TOT)[1]. A TOT state is also viewed as a temporary word-finding problem [Shafto et al. 2008], when a person is unable to recall a well-known work in a moment when it is needed, which often brings them some cognitive distress [Lovelace and Twohig 1990]. Also, TOT is often studied in the context of language and namely, phonology, given the person in TOT is guided by the partial phonological information [Burke et al. 1991; Rapp and Goldrick 2000; Levelt 2001], such as the person knows the initial letter of the word or number of syllables, but cannot complete the target word.

In alignment with the notion of TOT, the users in the study [Arguello et al. 2021] failed to recall a specific movie title. They were often guided only by the currently accessible (contextual) information fragments the users were able to recall, conforming to the outcomes of previous FOK-related works about the importance of the retrieved partial information in the working memory [Brewer et al. 2010; Koriat 1993]. From the point of further discussion, the study introduced a new perspective on how the user might perceive their IN which ultimately affects not only the articulation of the IN but the user's search behaviours as well. For instance, the reports showed that users often failed when solely relying on the SERP (Search Engine Retrieval Page), which urged them to consult their inquiries at different user forums. It opens up a new area of research supporting users in these states. In order to develop a strategy, further research is needed to understand a broader spectrum of users' cognitive states by their origin. Our research contributes to this aim with a *NeuraSearch* study applying rates on a scale of three Meta levels with FOK among them.

2.3. NeuraSearch Research

The rise of interdisciplinary research combining IR with the neuroscience insight [Mller-Putz et al. 2015; Mueller et al. 2008; Gwizdka et al. 2019] termed as NeuraSearch [Moshfeghi 2021] was demonstrated by successful applications in areas of relevance judgment [Allegretti et al. 2015; Pinkosova et al. 2020; Eugster et al. 2016; Pinkosova et al. 2023], IN realisation [Moshfeghi et al. 2016, 2019], search transitions [Moshfeghi and Pollick 2018], query construction [Kangassalo et al. 2019] IN satisfaction [Paisalnan et al. 2021, 2023]. Studies used variety of neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) [Moshfeghi et al. 2013; Moshfeghi and Pollick 2019; Moshfeghi et al. 2016; Paisalnan et al. 2021, 2022, 2023; Lamprou et al. 2023], magnetoencephalography (MEG) [Kauppi et al. 2015], and electroencephalography (EEG) [Moshfeghi et al. 2013; Kingphai and Moshfeghi 2021; Jacucci et al. 2019; Allegretti et al. 2015; Kangassalo et al. 2019; Jimenez-Molina et al. 2018; Gwizdka et al. 2017; Kingphai and Moshfeghi 2023].

[1]TOT state is generally seen as a stronger instance of FOK [Schwartz and Metcalfe 2011] with user having a strong feeling of imminent retrieval [Maril et al. 2003]

Our work was motivated by a series of fMRI studies concerning the processes behind the IN realisation by Moshfeghi et al. [Moshfeghi et al. 2016, 2019] and Moshfeghi and Pollick [Moshfeghi and Pollick 2019]. Due to the application of fMRI's high spatial resolution, all these studies were able to identify the topological distribution of processes discriminating between IN and no-IN. The researchers [Moshfeghi et al. 2016] revealed a signature region, posterior cingulate, with greater activity for IN-labeled condition. This region is known as a critical hub in orchestrating large-scale networks. Furthermore, they discovered predictive capabilities of fMRI-captured data in IN realisation [Moshfeghi et al. 2019]. This series culminated with the introduction of the "Neuropsychological model of information need realisation" [Moshfeghi and Pollick 2019] consisting of three interrelated components: (1) Memory Retrieval, (2) Information Flow Regulation and (3) Perception. This model is particularly relevant to our work since it discusses the involvement of regions inherent to factual searches in memory and metamemory context as part of Components 1 and 2. These play a vital part in creating a link between internal (memory) and external search, and they suggest the involvement of metamemory functions behind the realisation of IN. Our study expands on these works with the present investigation of the temporal dynamics of the brain activity subserving metamemory functions behind IN realisation. Relevant to such an aim is the EEG technique that is effective in capturing brain activity of underlying complex cognitive processes with high temporal resolution [Luck 2005]. Furthermore, the current development and availability of portable EEG devices strengthen their applicability as the signal input in Brain-Computer Interfaces (BCI) systems [de la Torre-Ortiz et al. 2020]. Several NeuraSearch works manifested the usability and effectiveness of the EEG technique. For instance, Kangassalo et al. [Kangassalo et al. 2019] investigated the neural correlates elicited while reading words with different specificities and found that term specificity was associated with amplified brain activity. Neural correlates emerged between 200ms to 800ms after the term has been presented. Hence, a user is capable of naturally recognising between terms which could help them to discriminate particular documents or construct queries. A recent EEG study by Pinkosova et al. [Pinkosova et al. 2020] benefited from employing EEG during the investigation of grades of text relevance with the ability to capture even the smallest variances between groups. The study reported significant differences in cortical activity associated with common ERP components (P300, N400, P6) across three grades of relevance (high, low, and non-relevant). These differences suggest that during graded relevance feedback, a variety of cognitive processes are involved to different degrees. Recent efforts in the NeuraSearch involved the applications in the context of recommendations or users' implicit feedback. For instance, the study by Davis et al. [Davis III et al. 2021] collected neurophysiological signals via EEG based on a series of visual stimuli with the aim to prove the feasibility of the brain signal as an information source in recommender systems. As a result, EEG signal could be used to infer user preferences and moreover, the potential utilisation of EEG signal used for collaborative filtering was demonstrated. In the next EEG study by Ye et al. [Ye et al. 2022], EEG signals were acquired during several search tasks which assessed their applicability as the searchers' non-click behavioural signals. The results showed the effectiveness of EEG signals to infer an estimation of the non-click results, such as usefulness.

For our study, we framed a data-driven analytical framework to identify and analyse the ERP components elicited during the sequential stimuli processing. The framework is described in Section 4.5.

3. PRELIMINARIES OF EEG AND ERP

The human brain generates small electrical activity on the order of a millionth of a volt. Electroencephalography (EEG) is a procedure for capturing this activity in real-time with a high temporal resolution of data collection. Time frequency (or sampling rate) is the measure of data sampling (e.g., 500 Hz/s). The sensor that is attached to a specific location of the skull surface to capture the cortical electrical activity is called an electrode and is usually made of sintered Ag/AgCl material. A common approach is to use an "EEG cap", made of elastic light-weight fabric, as the recording interface on top of which multiple electrodes are attached in order to get a signal originating from different areas of the brain. The electrode configuration on each cap follows the standardised "10:20 System of EEG Placement" [doi 1961] as depicted in Figure 3 which allows comparable results of spatial activity between subjects within a study as well as between the studies. The emerging technology of portable EEG headsets represents an alternative to a laboratory-based setting allowing us to conduct user studies simulating close-to-natural scenarios [Andres et al. 2020; Lin et al. 2014; de Lissa et al. 2015]. In both cases, the acquired data must go through a data pre-processing pipeline (see Section 4.5.2) to increase the Signal-to-Noise Ratio with the noise imposed by "the artefacts" originating from inside the body, such as heart activity, eye blinks, eye movements, facial and other muscle movements amplifying the signal.

3.1. EEG Glossary

Event Related Potentials (ERP) is a common approach to analysing EEG data based on averaging EEG response waveforms, time-locked to stimuli onset (start) and offset (end), across people and trials. **ERP Component** then represents a deflection from the baseline of EEG activity denoting neural activation or deactivation linked to some form of neural processing e.g. a cognitive function. The standard convention for labelling ERP components is to use: 'Letter which refers to the polarity of the component: Positive (P) or Negative (N) and 'Number, which refers to the time point on the series where this deflection reaches its local maximum, e.g. component N1 meaning negative deflection peaking at 100 ms post-stimulus.

Data Epoch is the time window within which the relevant brain responses, i.e. ERP Components, are expected to emerge. In our experiment, a typical epoch expanded from 200 ms pre-stimulus onset to 800 ms post-stimulus onset to cover the stimuli presentation time and the baseline activity (see Section 4.5.2).

Time Window as specific selections of the time series, i.e. epoch, that captures particular ERP components. This allows an investigation of the temporal dynamics of the relevant brain responses.

Region of Interest (ROI) representing a set of neighbouring electrodes that jointly contribute to a particular ERP component linked to the investigated function. The topological distribution of ROI (Figure 3) allows for the investigation of the spatial dynamics of relevant brain responses.

3.2. Prerequisites to ERP Analysis

ERP Analysis focuses on extraction and analyses of the amplitude of an ERP component to contrast between the given experimental conditions in a study. In general, the amplitude of an ERP component reflects the voltage elicited by the neural activity giving rise to the ERP component. The higher the voltage (higher negativity or positivity) the higher will be the ERP amplitude indicating a greater amount of neural resources (activity) recruited to support the specific neural operation [Kappenman and Luck 2015]. When an ERP component measured during two experimental conditions is compared, the resulting differences can inform about the spatio-temporal properties of the neural activity subserving the investigated RQs.

4. METHODOLOGY

4.1. Experiment

4.1.1. Design. We used a within-subjects experimental design, in which participants performed a Q/A Task. The dependent variable was the mean amplitude of relevant ERP components drawn from the EEG signals synchronised with the Q/A Task. The main aim of the experiment was to evaluate the modulations in the brain activity posed by the three pre-defined Meta levels (1. KNOW (I know), 2. FOK, 3. NKNOW (I do not know)). These were linked to the participants' responses which were controlled by responding to questions viewed on the screen. Meta levels represented the independent variable in the study: "KNOW" (I know) meaning a successful recall, "FOK" meaning a temporary inaccessibility to recall accompanied by FOK and "NKNOW" (I do not know) meaning recall failure.

By limiting the response space to three levels we had control over the categorisation of participants and the information processing associated with these levels. For each level, we extracted the relevant ERP activity (refer to EEG Glossary in Section 3).

4.1.2. Q/A Dataset. We constructed a data set of 180 questions of general knowledge taken from the following sources (1) combination of TREC-8 Q/A Track and TREC 2001 Q/A Track [2] (widely applied in studies in information retrieval [Moshfeghi et al. 2016]) and (2) B-KNorms Database[3] (used in cognition and learning studies [Chua et al. 2017]). Two independent assessors evaluated the questions' difficulty (Cohens Kappa: 0.61). They were tasked with judging if the question was generally easy or difficult to recall the answer right away. We selected 120 questions used as the input to the Q/A system with the matching annotators labels. Additional five questions were used for the practice session. The questions were of the open domain and closed-ended answers. Here is an example of a difficult question from the dataset: "What is the length of the coastline of the state of Alaska?"; and an easy question "What primary colours do you mix to make orange?". They covered a diverse range of categories: History, Science and Technology, Geography, Culture and Art. The question length was measured by the number of words the question consisted of. The question length ranged from three to thirteen words. Some of the questions taken from source (2) were syntactically modified to fit the question length limit. Additionally, we manually validated each answer using a search engine to ensure that selected questions were still valid and not ambiguous. The order of the questions was randomised for each participant. The question length (measured by the number of words the question consisted of) resulted from 3 words to 13 words. Some of the questions taken from source (2) were syntactically modified to fit the question length limit. Investigating question length and question category as potential factors did not confirm any significant impact on the investigated phenomenon.

Question Difficulty. The questions were equally distributed between easy (60) and difficult ones (60). This classification was used to manipulate the distribution of the participants responses in order to achieve the requirements of our data analytical methods. Specifically, we aimed to create balanced trials, or at least to have sufficient data across the investigated factors where the participants would likely experience scenarios of different perceptions of knowledge triggered by different levels of difficulties. As our study is concerned with memory and, in particular, knowledge, easy questions might trigger more of the initial Know-type responses, whereas difficult questions might trigger more of Dont know-type responses. Also, in the case of investi-

[2]https://trec.nist.gov/data/qamain.html
[3]http://www.mangelslab.org/bknorms

gation concerning FOK, the factors, such as input difficulty [Chua and Solinger 2015], input familiarity [Schwartz and Metcalfe 1992] or contextual information [Schwartz et al. 2014] and individual knowledge [Raju et al. 1995; Hadar et al. 2013] similarly modulate the levels of FOK. Accordingly, the question difficulty attribute was chosen to help to drive this effect. Apart from the control of the question difficulty, we compare our study with the traditional Q/A setting, as used in past NeuraSearch studies [Moshfeghi et al. 2016; Allegretti et al. 2015; Gwizdka et al. 2017]. In the binary system, each participant's response represents a conscious decision between "I know" and "I do not know" (analogy to our variables KNOW and NKNOW). Meanwhile, the inclusion of the FOK level modulates the response space and, moreover, represents the intersection between these two extreme levels considering the participant's natural feeling of perceived uncertainty [Hart 1965]. That is, the participant can consider the future likelihood of the recall in their decision. For instance, we expected higher ratios of FOK when the participant's strong feeling of a later recollection prevails [Yaniv and Meyer 1987] over the choice of NKNOW, which would demonstrate balanced trials.

Nevertheless, the question difficulty was not used as an independent variable in the currently presented data analytical model since we did not investigate its effects on cortical activity. In other words, we did not contrast the ERP response broken down by the question difficulty as it was used purely as the technique of data control. Further investigation of this variable remains a possible future extension of this study.

4.2. Procedures

Ethical permission was obtained from the Ethics Committee of Computer and Information Sciences at the University of Strathclyde. The experiment was performed in a research laboratory setting. All participants fulfilled the inclusion criteria to take part in the study, i.e. healthy people between 18 55 years, fluent in English, without any prior or current psychiatric or neurological conditions that could influence EEG signals.

In the beginning, participants were distributed an Information Sheet containing all the information about the experimental task (described in Section 4.2.1) in which they were going to take part. In particular, they were made aware of the general purpose of the study, and the design of the task (e.g., question-answering scenario, sequential presentation of stimuli) and were given a step-by-step explanation of the task structure. Also, the sheet described the EEG technique in general and informed them about its application on their scalp in order to monitor their brain activity. In addition, the participants were explained their rights (e.g., the right to withdraw at any time or ask for a break during the task).

The experiment started with two questionnaires requesting participants' demographic information and inquiring about their habits with information searching and search engines. After that, the participants were prepped for the task by having a researcher fit a number of electrodes to their scalps. To ensure that all the participants had a good understanding of the task, they underwent a practice session. The practice session consisted of five questions not used in the main task. This section was not limited in time, and participants were allowed to repeat it if required, until they felt comfortable to proceed to the main session. In the main task, question order, as well as the answer choices on the screen, were randomised across the participants. There was no time limit to provide the responses, which were entered by the participants via button press using three keys previously allocated to each option. Two breaks were provided (after completion of 1/3 and 2/3 of the questions) to avoid fatigue. Participants were asked to remain still and minimise any body movements, particularly blinking, as these represent noise-introducing artefacts to the brain signal.

Recording conditions were kept constant across participants. After the main session, there was a debriefing session. Participants were required to fill out a final post-task questionnaire related to their subjective perception of the task. A pilot study was conducted to ensure that the experimental procedure worked smoothly and the developed Q/A system ran correctly. Feedback from the participants in the pilot study was used towards the procedure improvements.

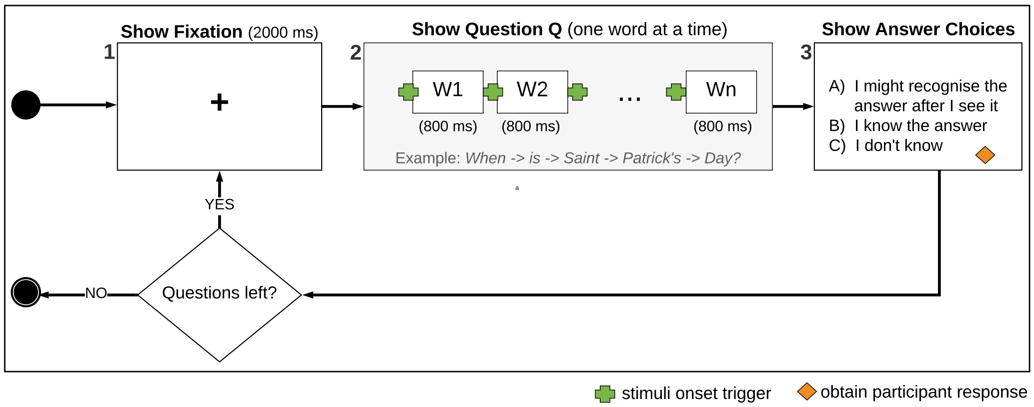


Fig. 1: Diagram of the task structure with an example of the sequential presentation using 5-word-question length stimuli.

4.2.1. Procedure of the Main Experiment Task. Figure 1 illustrates the Task sequence of sections relevant to our RQs and data here presented. Trials followed the same order of steps: Step 1 Fixation Cross, Step 2 *Question Presentation* and Step 3 *Meta Levels Judgment*. In Step 2 we captured the brain activity of participants during the sequential sentence reading, i.e. information processing. Step 3 captured participants' explicit responses, which were used to encode the signal into three Meta levels. Sequential presentation of a stimulus has been applied in studies examining neurological correlates of reading [Dimigen et al. 2011], as well as in IR-related studies of relevance [Pinkosova et al. 2020] or query construction [Kangassalo et al. 2019]. Its aim is to have control over free-viewing and to minimise the presence of any confounding artefacts (i.e., saccades).

The trial started with viewing a fixation cross in the middle of the screen for a duration of 2 000 ms that indicated the location of the next stimulus on the screen. Next, participants viewed a word-by-word presentation of a question randomly selected from the data set. Sequential presentation of the stimulus has been a typical approach applied in ERP studies examining neurological correlates of reading [Dimigen et al. 2011]. As a result, the ERPs were time-locked to the word onset presentation. Participants were instructed to read individual words that formed a question. Words on the screen were presented using a Fixed Rapid Serial Visual Presentation (fixed-RSVP) of 800 ms for each word. As previous studies of sentence processing [Hagoort 2003; Ditman et al. 2007] pointed out, a ratio above 700 ms applies engagement of higher cognitive abilities. These are important for us as we want to capture the human information processing and extract EEG signals associated with the same Meta level.

Literature [Ditman et al. 2007] also suggests another approach, i.e. self-paced reading methodologies, to allow for a more natural-like reading, which takes into consideration the fact that the longer or more difficult words require more time to process. We, however, justify our reasons for using fixed-RSVP: (1) to time-lock the stimuli presentation to get an equally lasting signal from processing each stimulus separately and (2) to reduce the effect of processing time differences. The duration of the word presentation was tested in a pilot study to affirm our settings.

Next, after all the words that constituted a question ran on the screen, a new screen appeared in front of them asking them to provide a response, indicating their state of knowing (Step 3). They were instructed to respond by selecting one of these options, stated in random order: A. *I know the answer*, B. *I might recognise the answer after I see it*, C. *I do not know the answer*. Option A stands for successful recall (KNOW). Option C means retrieval failure (NKNOW). Finally, option B signalises that the participant cannot immediately recall the answer and indicate, thus, their FOK, i.e. they feel as recognising it later. A similar recognition-based prompt was used in a question-answering scenario investigating FOK based on the varying difficulty of the stimuli [Chua et al. 2017]. Aligned with this approach, we asked the participants to acknowledge (indirectly) their FOK via the judgment of their future recognition performance. In this sense, FOK is interpreted in relation to the future ability to recognise, conforming to the nature of FOK [Brewer et al. 2010; Thomas et al. 2016]. Recognition tasks are commonly applied during stimuli-based FOK studies as a form of verification or accuracy tests of the initial FOK judgments [Costermans et al. 1992]. In a similar fashion, a response booklet was used in [Morson et al. 2015] for obtaining participants' FOK measures. Here, a binary form of FOK was used asking participants: *Would you recognise the answer if it was given to you?* with two answer choices *Yes* and *No*.

4.3. Participants

Data were collected from 24 healthy university students. As our data analysis (see 4.5) relies on individual averages, we need a sufficient sample in each Meta level. Data from two participants were excluded from the final data sample as their responses were highly skewed in their respective Meta levels. The process is justified in 4.5.1. Within the remaining 22 participants, there were 16 females (73%) and six males (27%) with an age range between 18 and 34 years and a mean age of 23 years ($\pm$4). Undergraduate students accounted for up to 68% of all participants, followed by 18% being PhD students. Almost 60% of all participants studied for Psychology or Psychology Combined degree followed by 27% of students of Computer Science or Mathematics. Participant demographics, such as age, were not balanced as our RQs did not consider these as independent variables. The participants were volunteers and received no monetary payments but were eligible for academic credits. Participants completed the task (without breaks) on average in 44 min (sd=4.62, med=43.40).

4.4. Data Acquisition

4.4.1. Apparatus. The Q/A system was developed with the behavioural research software e-Prime2. The main experimental task was synchronised with an EEG system. A 40 electrodes NeuroScan Ltd. system with a 10/20 configuration cap was used for data acquisition. EEG was recorded with a sampling frequency of 500 Hz. Impedances were kept below 10 kΩ, and signals were filtered online within the band of 0.1 - 80Hz. EEG recordings were subsequently pre-processed offline using toolbox EEGLAB version 14.1.2 [Delorme and Makeig 2004] executed with Matlab R2018a. A further stage of statistical analyses was done in RStudio with R 3.6.1.

4.4.2. EEG Data synchronisation. EEG signals were time-locked to the word presentation, as shown in Step 1 in Figure 1 due to the fixed-RSVP approach of 800 ms, which has been previously reported in 4.2. In order to associate EEG recordings with behavioural data, we applied synchronous triggers, i.e. unique identifiers for each trial. Triggers were sent to a separate file at the onset of each word (as depicted by a green cross icon in Figure 1) and at the time of the button press indicating the participant response (depicted by an orange diamond in Figure 1).

By design, we eliminated signal contamination by neural correlates corresponding to motor responses (i.e. hand movement to make a button click) as a response-preparation component as it generates "a noise" affecting the underlying brain signal [Kappenman and Luck 2015]. The participant was required to make an explicit response only after the entire question was presented on screen. Furthermore, randomisation allowed to eliminate any order bias and response tendencies.

4.5. ERP Analysis

A combination of exploratory and component-driven approaches confirmed the presence of reproducible and stable ERP components linked to the Q/A Task. To investigate the spatio-temporal dynamics of brain responses, we i) split the epochs into smaller time windows aligned with relevant ERP activity and ii) selected relevant ROIs where such activity reached the significant threshold. We framed such procedures in a way that allowed us to achieve unbiased results and avoid Type I error. Details are provided in Section 4.5.3 and 4.5.4.

4.5.1. Sample Size pre-processing. Our exploratory methods rely on the individual averaged ERP waveforms for each level. In order to create average ERP waveforms per each investigated Meta level, we need a sufficient data sample at each Meta level. Prior to establishing how to proceed with data pre-processing, we observed the behavioural responses, i.e. analysing the distribution of responses in each Meta level per participant and averaged across the participants (see Section 5.1. Since the individual distributions showed large differences between the Meta levels, consequently, we needed to set what data samples are suitable for the analysis. ERP waveforms are considered quite stable in time if they are underpinned by a large number of data epochs [Luck 2005]. The question was, then, for us how many trials a single participant must have recorded in order for level-dependent ERP components to project [Kappenman and Luck 2015], i.e. observe a clear manifestation of ERP waveforms while reducing the contamination by noisy records. We checked the individual records for each participant and sorted them in ascending order by the number of records at each level. Participants with the lowest proportion of responses were selected, and their ERP waveforms were visualised. In addition, we observed the graph of the activity on the power spectral density. Our findings showed that stimulus-triggered activity emerged when averaging data epochs from at least 12 trials (representing 10% of all trials participants were subjected to), which we then set as our threshold. Altogether, 22 participants fulfilled this condition.

4.5.2. Data pre-processing. Individual participant data were pre-processed using the pipeline constructed according to guidelines for the standardisation of processing steps for large-scale EEG data [Bigdely-Shamlo et al. 2015]. Before passing the data through a high-pass filter at 0.5Hz and then a low-pass filter at 30Hz, we removed the power line noise at 50Hz. Next, we down-sampled data to 250Hz. We then proceeded to reconstruct a low-quality EEG signal of selected electrode/-s whose recordings were found to be very noisy or their recording was interrupted. After that we used average re-reference, suggested as an appropriate approach [Dien 1998] in a case of data-driven exploratory analyses of ERP components and ROIs given by the novelty of the task where associated neural activity is unknown [Kappenman and Luck 2015], such as ours. In the next step, we performed Independent Component Analysis (ICA), a data-cleaning technique used to separate the noise-introducing artefacts from the genuine brain signal, i.e. the sole brain effect to stimuli. Completion of ICA resulted in an artefact-free signal which was then epoched, i.e. selecting events of interest, from 200ms pre-stimulus presentation to 800 ms post-stimulus. All epochs were baseline-corrected using the -200 to 0 ms window using the baseline activity prior to the onset of the first word of each question (represented by Screen W1 inside Step 2 in Figure 1). We subtracted the average of the points from the baseline period prior to the onset of the first word of a question from each point in the question presentation waveform. It is a common technique to remove DC-offset, i.e. compensate for signal drifts in electrophysiological recordings [Alday 2017].

After that, we averaged data epochs of each participant and of each Meta level and thus, generated grand averages ERP waveforms per Meta level for each participant. These average participant data entered the further stages of the statistical analysis.

4.5.3. Identifying Regions of Interest (ROI). Kappenman and Luck [Kappenman and Luck 2015] suggested dealing with both the selection of time windows and ROIs by separating statistical tests for each time point at each electrode, combined with correction for multiple comparisons. Following this approach, we searched for significant differences across Meta levels with a combination of a 2-sample paired Monte Carlo permutation test and non-parametric bootstrapping running 10,000 permutations[4]. The outcome of each pairwise comparison was a set of significant ($p<0.001$) electrodes and their assigned time point where the activity significantly differed across the compared Meta levels. An electrode that was found in all three sets we called a common electrode as it represents common modulation of brain activity in that particular time window. As electrodes can be part of clusters or hubs, where it was possible, we assigned electrodes to an ROI based on their spatio-temporal properties, i.e. local proximity (according to Figure 3) and found significance within a specific time window.

4.5.4. Time Windows. To set the boundaries of time windows capturing relevant ERP components, a combination of the unbiased procedure described above and a data-driven approach was followed. As suggested by Kappenman and Luck [Kappenman and Luck 2015], we averaged all the epochs corresponding to the three Meta levels across all ROIs and participants. This reflects the overall brain responses regardless of task conditions and topological distributions with the baseline set y=0. From these grand waveforms, we selected the time points where the waveforms, i.e. ERP components, were abandoned and returned to baseline. Figure 2 depicts a grand average waveform from a front-central ROI. The horizontal black line represents ROI's temporal grand average which we used as a baseline reference. Red points were generated as boundaries for splitting the timeline into smaller time windows, each containing a component of the same polarity. We then calculated the mean signal within such boundaries for each relevant ROI.

4.5.5. Statistical Methods. Our main comparative measure is the mean ERP signal, calculated as the mean of the ERP activity, precisely the amplitude that describes the ERP activity, which occurred within a particular time window (see 4.5.4) and significant ROI (see 4.5.3). We created a mixed linear model for each time window with the parameters: "Meta levels" as the independent variable, "Participant" as the random variable, and "Mean ERP signal" as the dependent variable. In order to test if participant score (i.e., elicited mean signal measured in ROI) varied significantly across Meta levels, we applied ANOVA repeated measures test with a 3-level factorial design for each time window and for each significant ROI.

[4]A solution for multiple comparison problems and does not depend on multiple comparisons correction or Gaussian assumptions about the probability distribution of the data.

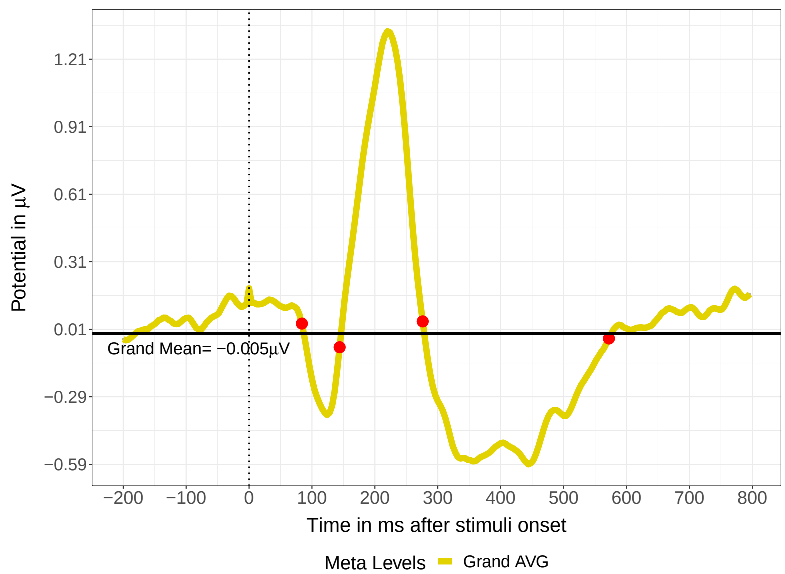


Fig. 2: Identifying time windows of ERP components based on the grand ERP waveform. Here, the ERP waveform is generated for bilateral front-central ROI.

Data were tested for normality and sphericity. We used the Greenhouse-Geisser correction when the dependent variable did not meet the sphericity criterium. Post-hoc tests applied Bonferroni correction for three pairwise tests.

5. RESULTS

5.1. Behavioural Responses

We calculated the distribution of Meta levels according to participants' responses and then aggregated these values. The general distribution shows that 41% (sd 10.8) of responses were of FOK with an average response time of 1.91 s per question, followed by 30% of KNOW responses (sd 14.1) with an average response time of 1.89 s. On 29% (sd 11.1) of the trials, participants responded with NKNOW with an average response time of 1.90 s. In order to test if response time varied across Meta levels, we ran ANOVA repeated measures test. However, no significant differences between the average response times have been found.

5.2. Task Perceptions

Participants perceived the task mostly as Interesting (58%). In relation to the difficulty of the overall experiment, the task was perceived as relatively Easy (54%), followed by the perceptions of some degree of difficulty (Not so Easy 21%, Slightly Difficult 17%). Those who perceived some degree of difficulty also found the task to some degree Challenging (21%). In general, the task was not perceived as Stressful (4%) nor Familiar (4%). In general, the participants agreed that the Q/A dataset was an appropriate mix of easier and more difficult questions of general knowledge. Additionally, we select a few participants' comments which expand on their perceptions with the Q/A dataset: *"Topics varied widely which was very interesting as there was quite a mix of things I knew and things I did not."*; *"Some answers I thought I knew and I was wrong and vice versa."*

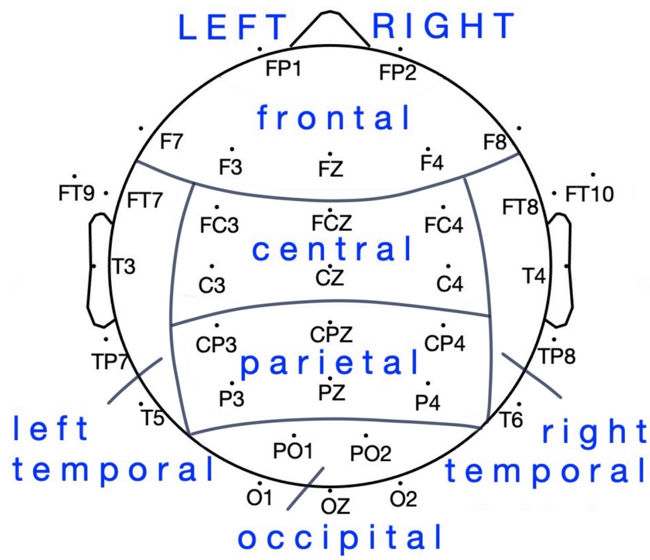


Fig. 3: Placement of electrodes on EEG cap and their regional assignment (ROI) as used in our study.

5.3. ERP Findings

According to Section 4.5.3 significant ROIs were identified. Following the approach in Section 4.5.4 we identified time points where the ERP deflection crosses the grand mean baseline. We identified four ERP components with their latencies as: N1 (with earliest onset at 84 ms, the latest offset at 168ms), P2 (earliest onset at 144 ms, the latest offset at 284 ms), N400 (with earliest onset 264ms, the latest offset 584 ms) and P6 with the early onset at 556ms. Despite the variations in the onset and offset of a component, we created one set of time windows common for significant ROIs. This way, we were able to capture the majority of the ERP response within the common window. The time windows were set: 1) 90 - 150 ms, 2) 150 - 270 ms, 3) 270 - 570 ms and 4) 570 - 800 ms.

The average activity of such components across relevant ROIs was then submitted to ANOVA to test their discriminative power across Meta levels. The main findings of significant pairwise ERP modulations are presented in Table I. The first column *Time Window* shows the temporal intervals where ERP components occurred (*ERP*). The column *ROI* specifies the location where the mean of the corresponding ERP shows statistical significance. The column *F value* quantifies the value of the statistical test with (2,42) degrees of freedom. The column M_{diff} compares the mean values of two significantly different Scenarios identified by the pairwise post-hoc tests. At last, column *p* shows the level of statistical significance (p-value). Figures 4 and 5 complement this table by illustrating the corresponding ERP waveforms at the significant ROIs. Each waveform represents the elicited potential measured during the 800 ms window per certain Meta level with a zoom on a particular significant time window. Each Meta level is encoded by a specific colour and a marker. The scales are uniform for all corresponding plots. Additional Figure 6 shows the levels of elicited mean potential for significant ROIs.

Following the chronological latency of the ERP components, we now describe the main findings.

Table I: Significant differences in ERP amplitudes and the pairwise contrasts (p-value adjusted to three 3 pairwise tests using Bonferroni corrections <0.05 *, <0.01 **)

Time Window	ERP	ROI	M_{diff}	F value	p
90 - 150 ms	N1	LF	$\bar{x}$(KNOW)=-0.40μV, $\bar{x}$(FOK)=-0.12μV	F[2,42]=4.32	*
		RCP	$\bar{x}$(KNOW)=0.14μV, $\bar{x}$(FOK)=-0.10μV	F[2,42]=4.34	*
150 - 270 ms	P2	RFT	$\bar{x}$(KNOW)=-0.07μV, $\bar{x}$(NKNOW)=0.11μV	F[2,42]=3.57	*
270 - 570 ms	N4	FT	$\bar{x}$(KNOW)=-0.27μV, $\bar{x}$(FOK)=-0.39μV	F[2,42]=3.50	*
		PO/O	$\bar{x}$(KNOW)=0.45μV, $\bar{x}$(FOK)=0.63μV	F[2,42]=3.44	*
570 - 800 ms	P6	RC	$\bar{x}$(KNOW)=0.06μV, $\bar{x}$(NKNOW)=0.16μV	F[2,42]=3.94	*

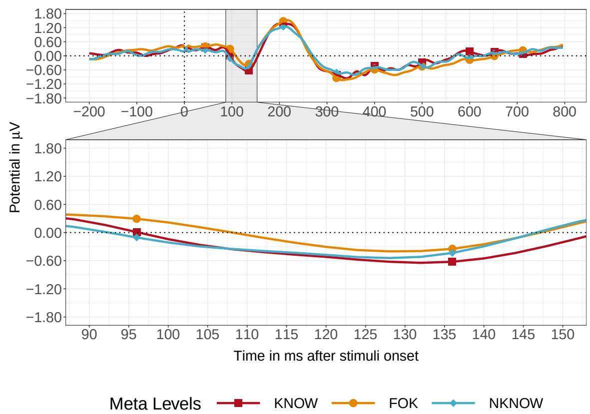
(For spatial reference of ROIs see Figure 3: L - Left, R - Right, F - Frontal, C - Central, T - Temporal, P - Parietal, O - Occipital.)

5.3.1. Time Window 90 - 150 ms of N1 component. Left frontal (LF) activity differed significantly between KNOW and FOK levels. Furthermore, activity in right centro-parietal (RCP) ROI was also found to discriminate between KNOW and FOK levels. In both ROIs, significantly greater mean negativity (p<0.05) of N1 amplitude was exhibited for the KNOW level. The contrasting ERP waveforms in LF and RCP ROI are depicted in Figures 4a and 4b, respectively.

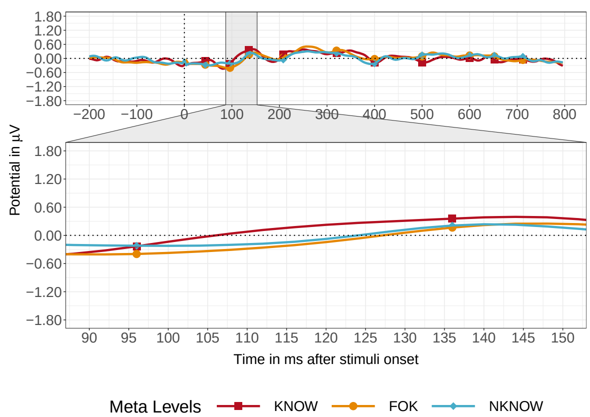
5.3.2. Time Window 150 - 270 ms of P2 component. Outcomes of ANOVA and subsequent pairwise contrasts revealed significant differences between the neural activity for KNOW and NKNOW levels measured within the right front-temporal region (RFT), with NKNOW level exhibiting significantly (p<0.05) higher mean activity associated with the P2 component. The P2 waveforms of corresponding Meta levels are illustrated in Figure 4c.

5.3.3. Time Window 270 - 570 ms of N400 component. We observed a widespread distribution of activity involved across multiple brain regions manifested as the N400 component. ANOVA revealed the significant impact of anterior-posterior ROIs on mean activity within this time window, precisely sourcing from electrodes in bilateral front-temporal ROI (FT) and electrodes in occipital ROI (PO/O). Post-hoc tests specified that these effects were significant between KNOW and FOK levels, with FOK levels exhibiting a significantly (p<0.05) greater activity in both ROIs (greater negativity of P2 in FT and greater positivity of P2 in PO/O). Figures 5a and 5b depict the ERP waveforms in both ROIs.

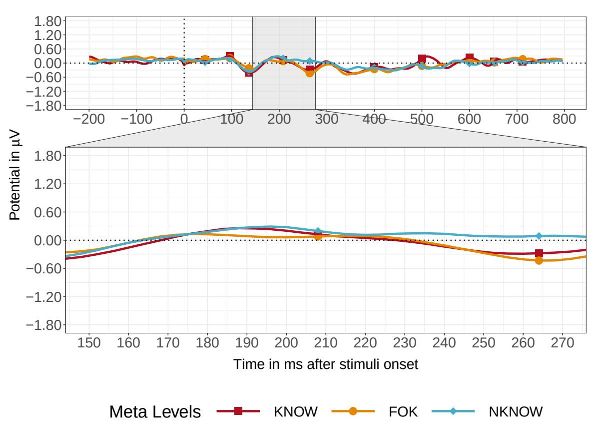
5.3.4. Time Window 570 - 800 ms of P6 component. Results of ANOVA revealed a significant difference in mean activity across Meta levels in the right central brain area (RC). Post-hoc tests identified that the mean amplitude described as P6 differed significantly between KNOW and NKNOW levels, with the NKNOW level exhibiting significantly (p<0.05) higher mean of P6 amplitude in contrast to the mean signal of KNOW. Figure 5c shows the ERP waveforms.



(a) N1 (90-150 ms) over LF ROI

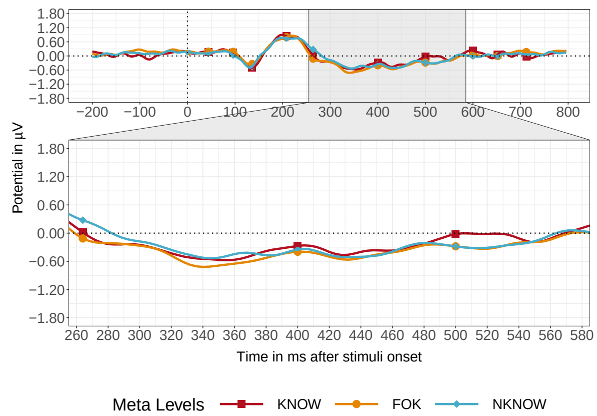


(b) N1 (90-150 ms) over RCP ROI

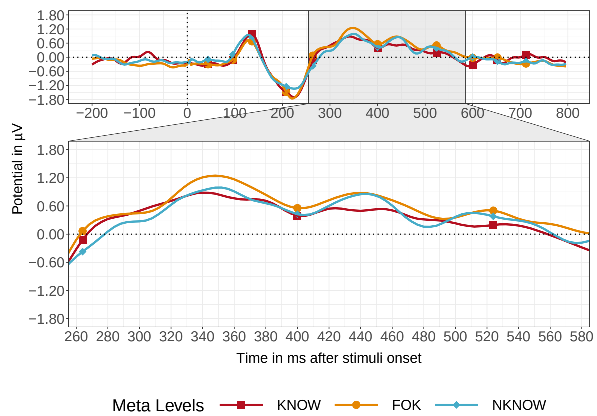


(c) P2 (150 - 270 ms) over RFT ROI

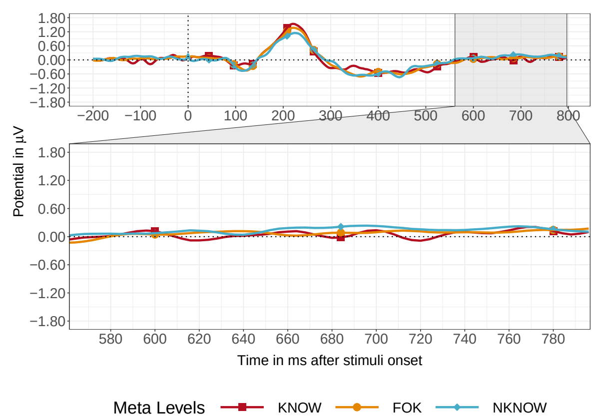
Fig. 4: ERP waveforms of Meta Levels with a zoom on time windows between 90 - 270 ms over significant ROIs (as a result of ANOVA). Averaged over 22 participants.



(a) N400 (270 - 570 ms) over FT ROI



(b) N400 (270 - 570 ms) over PO/O ROI



(c) P6 (570 - 800 ms) over RC ROI

Fig. 5: ERP waveforms of Meta Levels with a zoom on time windows between 270 - 800 ms over significant ROIs (as a result of ANOVA). Averaged over 22 participants.

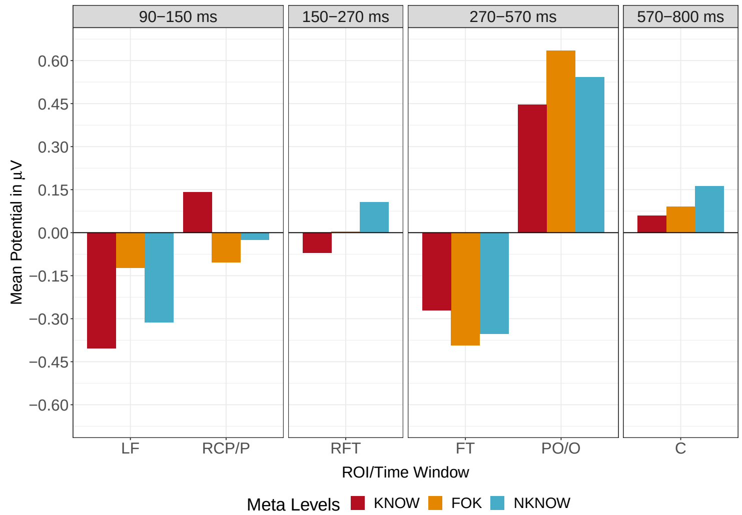


Fig. 6: Temporal contrast of mean potentials elicited at significant ROIs (L-Left, R-Right, F-Frontal, C-Central, P-Parietal, T-Temporal, O-Occipital)

5.3.5. Summary. Early activity linked to the N1/P2 complex indexed significant differences between KNOW and FOK over RCP and LF regions, which then propagated to FRT ROI to account for differences between KNOW and NKNOW. The highest activity linked to the KNOW level could indicate quick access to available knowledge, in contrast to the activity elicited by FOK and NKNOW state. The later activity of the N400 component was apparent over both anterior and posterior regions. Significant effects were triggered by a contrasting activity between KNOW and FOK levels. FOK judgments elicited greater amplitude of the N400 component at PO/O ROI and FT ROI. At the later processing stage, P6, we found involvement of a central (C) region underpinning the significant differences between KNOW and NKNOW levels, with NKNOW reaching a higher positivity of P6. In summary, in all time windows, we saw the involvement of KNOW level as a driver of the significant effects on the elicited signal with a widespread location, but a consistent frontal/front-temporal distribution that carries out the significant differences. Figure 7 maps the locations of ROIs (where significant pairwise differences between Meta levels were found) onto the brain topological graphs.

6. DISCUSSION

First, we addressed RQ1: *"Is there a clear, detectable, physical manifestation of FOK in the context of metacognitive states of knowledge (Meta levels)?"* by providing evidence of a consistent ERP output corresponding to the user's FOK state as well as two other Meta levels. Next, we addressed RQ2 *"Do the neural manifestations of these three Meta levels differ and how could the differences inform the context of user's ASK in IR?"*. We performed ERP analysis contrasting these Meta levels, each of which depicts the user's different states of knowledge. We now proceed to discuss the main findings of our study in more detail as well as their impact on IR.

6.1. Findings underpinned by cognitive processes

Our study identified four ERP components subserving different pre-defined Meta levels. The early activity was associated with the N1-P2 complex. Left frontal lateral

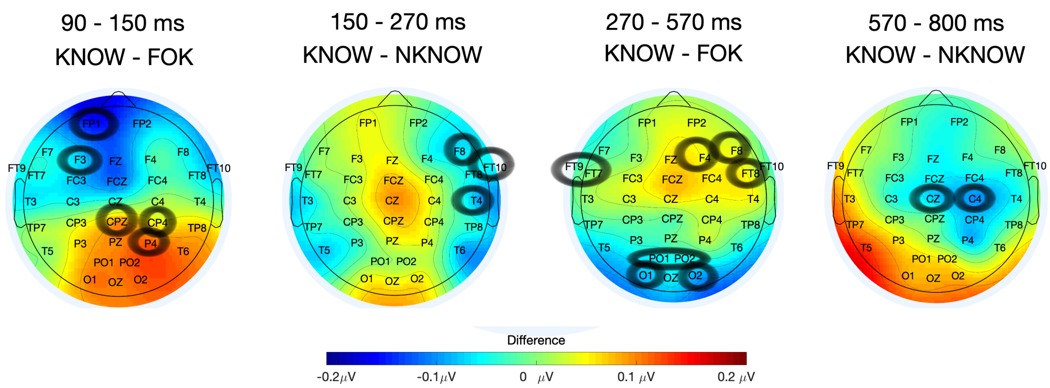


Fig. 7: Temporal topological plots of a difference between a pair of significantly different Metal levels highlighting the ROIs where this difference occurred (see Table I for reference).

distribution activity discriminated between KNOW and FOK before 150 ms post-stimulus. The frontal distribution is consistent with previous neuropsychological and brain imaging studies [Fernandez-Duque et al. 2000; Irak et al. 2019b,a] about the important role of frontal lobes in memory-monitoring processes. Here, the KNOW level recorded greater negativity of N1 over the remaining levels, which leads to a suggestion of quick access to assessment of knowledge which prompts the user to make a quick decision. Further, the high activity of KNOW propagates into the right front-temporal region to significantly separate this from the NKNOW level.

These early evoked components are thought to reflect the automatic stimulus processing influenced by attention and orientation processes [Paynter et al. 2009; Dien 2009]. The P2 component has generally been associated with the perceptual processing of stimuli [Paynter et al. 2009; Irak et al. 2019a], in particular, P2 might be an important driver to guide perceptual fluency (the ease with which perceptual processing takes place) and therefore metamemory judgments. Another study attributed the P2 component to an initiation of an attempt to recollect the study episode via episodic memory involving rapid assessment of familiarity, i.e. the ability to recall specific episodes for those stimuli which seemed to be sufficiently familiar [Diana et al. 2005]. This could potentially explain our findings of maximal positivity of the P2 component reached for KNOW and FOK responses, as the participants might have perceived the stimuli familiar enough to retrieve it from memory, either in full or a sense of prospective (later) knowing, related to FOK. Our findings of early brain responses are in coherence with the view by Paynter et al.[Paynter et al. 2009], who investigated ERP within a memory retrieval and found early rapid neural correlates emerged before a conscious awareness reaching point.

Negativity with the 270 ms onwards might correspond to the presence of the N400 component. At first, similar to our study, N400 was found to occur during word-by-word sentence reading [Kutas and Federmeier 2011], and in addition, our findings of a broad multi-region activation support its notion of a highly distributed neural source and leading to a further level of processing.

Significant activity was found to be distributed in front-temporal and parieto-occipital areas. The discriminative activity was again found between KNOW and FOK, however, FOK reaching greater values than the KNOW level. At first, the temporal lobe has been highlighted as an important source for the N400 [Irak et al. 2019a] and a switch to controlled functions when perceptual fluency drops. It might explain greater activity found for FOK level, as the user might be having more difficulties recalling the answer. This could be explained as enhanced attention to unexpected stimuli, which then gives rise to FOK. It might suggest a further level of processing in relation to the unexpectedness of stimuli and potential correlation with word familiarity.

Second, the distinction in the posterior N400 component centred over the parieto-occipital area might partially support the notion of a potential gateway mechanism. Through this mechanism, automatically triggered responses activate more controlled functions and possibly memory-driven functions, i.e. binding the internal representation of the input stimuli with the memory output, such as semantic or long-term memory. Similarly, Moshfeghi et al. [Moshfeghi et al. 2016] found a switch within sub-regions of the parietal region from internal sources to external sources when user realised their IN, making it a signature mechanism for IN realisation.

At last, late positivity prominent for NKNOW level could be attributed to P6. A partial explanation for this activity could be linked to memory processing as has been observed during memory recognition [Yang et al. 2019]. When syntactic integration does not render familiar signals, a more in-depth (later) process will be activated, which then gives rise to NKNOW. P6 was found to be sensitive to reading a series of dependent stimuli with different complexity, such as used in our study, so the reader has to recollect stimulus that appeared earlier [Kaan and Swaab 2003; Beim Graben et al. 2008]. To analogise with our findings, for stimuli of longer length and of higher complexity, recollection of previous (dependent) stimuli might have been triggered in order to assess their NKNOW state accurately. This could imply that it takes longer for a user to acknowledge their NKNOW state in contrast to previous states.

The sequence of N400 and P6 can be additionally interpreted within the frameworks for sentence processing and language comprehension, in particular, the two-stage Retrieval-Integration model by Brouwer et al. [Brouwer et al. 2012]. First, the retrieval part, reflected by N400, is modulated by the ease with which lexical and semantic information can be retrieved from long-term memory. With respect to our findings, the retrieval process affected KNOW with reduced N400. This effect suggests relatively easier processing for KNOW than FOK on the basis of the semantic association of the stimuli (words in the question) with the target (recalled answer to the question). Second, integration processes create syntactic and mental representations. The P6 is more likely associated with the effort needed to establish a coherent discourse of this integration [Brouwer and Hoeks 2013]. According to this account, the enlarged P6 for NKNOW talk about a more demanding integration required to integrate the stimuli with the less salient information as an output of the earlier processing stages. In contrast, the processing exhibited for the KNOW level moves in the other direction with the lowest P6 amplitudes.

In summary, there is a clear manifestation of ERP activity for all investigated Meta levels. As a focal point of our RQ1, the signature activity for the FOK level was detected and described by the ERP components. The significant spatio-temporal differences found across Meta levels inform about the differences in cognitive activity behind the user's realisation of the state of knowledge which answers the first part of RQ2. To address the second part of RQ2 about how we can utilise this information in the context of ASK variants, from their detectability to IR's support, we will look at the cognitive features and functions driving the differences between Meta levels.

6.2. Resolution of FOK and personalisation of IR

The majority of statistically significant findings were found contrasting KNOW (i.e. when we realise we know the information) and FOK level with the widespread activation throughout the course of information processing. This finding suggests that FOK is supported by different activities of neural operations and makes it a distinctive level in the processing of incoming information. No significant contrasts between FOK and NKNOW indicate little functional distinction between these two levels. This idea is supported by the nature of these levels since they are described as unsuccessful recall levels, i.e. in both cases the participants did not recall target information [Maril et al. 2003]. As we presented, the NKNOW level describes the state of potential IN, due to the generally accepted idea that “what one does not know” leads to the state of IN [Belkin 1980; Wissbrock 2004]. Inferring from this generally accepted theorem, our inclusion of a new variant of IN, FOK, was thus justified from a neurocognitive perspective as a relevant pattern of activity signifying IN. What lies ahead of IR research is to understand how to better support the users in their differing cognitive states of knowing, validating the idea presented in [Arguello et al. 2021]. Even the early iterations of the ASK-IR model [Belkin et al. 1982b] recognised that differentiating the retrieval mechanisms would be required to support variants of ASK [Belkin et al. 1982a].

Taking our data, we see the significant modulations already in the early rapid ERP components. These could be possibly linked to the underlying familiarity of the stimuli evoking the brain response. Familiarity is one of the main bases of a user’s increased performance in memory recall tasks, such as recognition [Hintzman and Curran 1994]. The literature [Shen et al. 2020] also showed that the stimuli familiarity affects the ease of information retrieval and subsequent processing associated with this information. In the IR context, the investigation of the familiarity of the user is an approach to the personalisation of IR [Muresan et al. 2006]. Topical familiarity has been studied in the IR context [Kelly and Cool 2002] and evidence showed the interaction effects with user search behaviour (e.g., use of information resources) and relevance judgements and, thus, considered a factor in information searching [Bates 1996]. Following the findings of our study, it is suggested that the gradient of familiarity impacts the final perception of the user’s state of knowledge, current or prospective.

Further research expanding on this idea would be beneficial to confirm these speculations, with the use of brain patterns of familiarity as a predictor of the user’s cognitive context. In addition, term familiarity has been a target of several ERP studies, with [Khurana et al. 2018] detecting different patterns of activity between familiar and unknown words. To extend this idea in the context of IN, the term familiarity can be helpful in disclosing which segments of the problem the user is more familiar with and vice versa. Searcher’s familiarity gives an indication about the user’s cognitive context as well as information preferences [Kelly and Cool 2002]. Consequently, such knowledge about the user can be used in even a pro-active way from the IR side [Bhatia et al. 2016]. For instance, it can contribute to reducing the information space and providing a personalised list of retrieved documents with respect to the accurate representation of the user’s state of knowledge. From the perspective of IR performance, this would mean an increased efficiency in satisfying IN by directly targeting what (portion of) information the user needs to know.

6.3. Implications for IR

IR process has expanded beyond its primary objective to provide the user with relevant information and is seen as an interactive problem-solving and sense-making process with intrinsic user’s cognitive context as an input [Ingwersen 1984; Kuhlthau 1991].

The present application of the interdisciplinary framework demonstrated an area of great potential for IR system design to objectively and proactively detect the surroundings of the user’s cognitive context [Ingwersen and Järvelin 2005; Ingwersen and Järvelin 2005]. On the whole, recognising the state of the user’s knowledge means for an IR system to possess information describing the user’s knowledge anomaly. The mapping of the information about the user's knowledge to the adaptive or pro-active retrieval process can follow, for instance, to limit the search space [Torbati et al. 2021] or address the area of overload of IR users, both information and cognitive (mental) workload [Belabbes et al. 2022]. The more accurate information the system possesses about the user, the higher the efficacy in assisting the user and reducing users' behaviours when feeling overloaded [Kingphai and Moshfeghi 2023]. As a response, an increase in confidence, a reduction in the searchers' effort and ultimately user satisfaction can be observed [Michalkova et al. 2023].

To put this idea into operation necessarily lead us to address the main component of the search, which is the user input, i.e. query or other forms of INs input. How to represent FOK (or any other variant of ASK) as a query? Could IR intervene and help the user, for instance in the area of query suggestions? As the research demonstrated [Arguello et al. 2021], the users often remember only episodic and event-related information and lack factual memory to construct a query. INs are described as information requests rather than system queries as users often miss the keywords that would help to mine the information documents. For this purpose, more research to understand the relation between FOK and other variants of ASK with the user information search behaviour are needed. Exploration of the search patterns, search habits and expectations should continue. Similarly, as was initiated in the qualitative investigation of TOT requests [Arguello et al. 2021]. For instance, FOK users might have different expectations of the retrieved results, as they possess some prior knowledge than users who do not. Since knowledge is a central element in these theories, knowledge self-oriented awareness (metamemory) can further explain IN variants that might lead to different information behaviours. The extension of the study would benefit from a user-based study with the users' active engagements in the study context.

7. CONCLUSIONS

The connection between ASK and the underlying awareness mechanisms can provide valuable insight into the origins of ASK. These can form a new perspective on how the users process INs and inform us about the user's variability of anticipations with IR system outcomes. According to our study, the inclusion of the user state of FOK allows for a more accurate specification of the anomalous state of knowledge considering FOK's natural proposition of positive future prospective performance. Our study provides an essential step in exploring a graded nature of the states of knowledge through the identification of neural drivers linked to three defined three Meta levels, i.e. (1) "I know", and (2) "FOK", (3) "I do not know". This study highlights an essential step in exploring the graded nature of states of knowledge through the identification of neural drivers linked to three defined Meta levels.

We developed a scenario for participants to perform a Q/A Task of general knowledge whilst their corresponding neural activity was recorded. Taking the spatio-temporal features of these data, we conducted discriminative analysis associated with different Meta levels. The patterns of early neural correlates suggest (subconscious) brain processes differentiating between the cognitive states of knowing. The results indicate that the ERP contain information about the user's state of knowledge in the context of a graded recall that is manifested before the user's awareness of their state of knowledge. Subsequently, it suggests that an IN realisation could happen at a subconscious level at its earliest state. Analysis of the latter activity across Meta levels revealed the sequential engagement of more controlled and effortful neurocognitive functions.

Regarding the FOK state, our data support that FOK has a distinctive neural manifestation and is detectable from the brain, which supports the variability of ASK on the neurocognitive level. As has been noted, FOK denotes a state that is naturally evoked and acknowledged by a person, which makes its role in defining the searcher's context promising to explore further. Subsequently, our work opens a follow-up expansion of investigations led by metamemory-induced IN states with a strength of familiarity as a potential indicator of the corresponding state. Furthermore, research expanding on our proposal could benefit from a definition of further granular states of FOK or experimenting with new sensory input modalities, such as auditory, which is especially relevant due to the significant growth and adoption of voice technologies in IS&R.

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