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Untangling Cognitive Processes in Academic Information Searching: Investigating Tool Gaps, Cognitive Load, and User Satisfaction

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Abstract

Academic information searching is a cognitively demanding activity requiring users to navigate complex decision-making, evaluation, and synthesis tasks. This study investigates how prior topic knowledge, perceived tool adequacy, and self-assessed search experience influence cognitive load, satisfaction, and confidence during domain-specific academic search tasks. Using a mixed-methods design, 31 participants engaged in authentic search scenarios, providing data via pre- and post-task questionnaires, including a modified NASA-TLX.

Findings demonstrate that prior knowledge significantly reduces mental demand, supporting Cognitive Load Theory and reinforcing the value of domain familiarity in search efficiency. Perceived tool adequacy was associated with significantly lower mental and temporal load, though it was not a reliable predictor of satisfaction. Meanwhile, self-rated confidence and efficiency did not significantly relate to cognitive experience, challenging assumptions in existing user experience models. Additionally, satisfaction was positively associated with cognitive engagement, particularly task complexity and concentration, rather than ease of use. These insights extend prior research by grounding cognitive load theory in real-world academic contexts and highlighting the importance of tool support beyond usability. The study underscores a shift from efficiency-driven design toward systems that actively augment cognitive engagement in knowledge work.

CCS Concepts

• Information systems → Information retrieval → Users and interactive retrieval • Human-centered computing → Human computer interaction (HCI) → Empirical studies in HCI

Keywords

Academic Information Searching, Cognitive process, Cognitive tool, Cognitive load, Tool adequacy, User satisfaction

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1 Introduction

In the modern workplace, information searching is a foundational activity for knowledge-intensive tasks, particularly in academic and professional contexts. Academic professionals frequently engage in complex search processes that demand substantial cognitive effort, encompassing analysis, evaluation, decision-making, and synthesis. While generic information search behaviour has been extensively structured and studied [1][2][3], academic searching remains underdefined in terms of its specific cognitive processes and support mechanisms—despite its central role in scholarly knowledge work [4][5].

Generic searches typically follow a structured progression—problem formulation, retrieval, evaluation, and reflection—often supported by basic search tools or general-purpose engines [6][7]. However, academic information seeking requires more than procedural search literacy. Tasks such as query refinement involve conceptual abstraction and flexibility [8], while source evaluation demands critical thinking, authority assessment, and contextual awareness [9]. These processes are iterative and metacognitive, requiring ongoing self-monitoring and strategy adjustment [10][11].

Beyond the search process, information use and synthesis activate higher-order cognitive functions such as analogical reasoning, inference, and working memory [12]. These operations are cognitively demanding and depend heavily on domain knowledge and experience. As search tasks grow in complexity, managing mental workload becomes increasingly important. Research by Gwizdka [13] and Kunz et al. [14] has shown that increased task complexity correlates with greater cognitive load, which can impair user satisfaction and performance if left unsupported.

Tool design plays a crucial role in this cognitive ecology. While traditional academic databases and discovery systems enable access, they often fail to scaffold deeper interpretive and synthesis tasks.

Several recent studies have pointed to these gaps. For example, Khazaei and Hoeber [15] proposed visual and citation-based enhancements to support exploration, while Chavula et al. [16] demonstrated how idea-generation tools can aid creative academic search. Other work has shown how cognitive complexity frameworks [17] and emerging AI-based assistants [18] influence search behaviour, task satisfaction, and outcome perception.

Despite these promising developments, few studies have explored how users experience cognitive effort, tool adequacy, and satisfaction when searching for self-defined academic tasks. Most existing research either uses predefined queries or simulation settings, which may not reflect the lived cognitive experience of academic information seeking [19]. Additionally, as Niwanputri et al. [20] noted, search and decision-making together account for nearly half of cognitive activity in professional work—further underscoring the need to support these processes more deliberately.

This study seeks to fill these gaps by investigating how academic users experience cognitive load, satisfaction, and perceived tool support during real-world, domain-specific academic searches. Drawing on structured pre- and post-task questionnaires, we examine the influence of topic knowledge, tool adequacy, and search confidence on users' cognitive and affective experiences. The findings aim to inform the design of cognitive tools that better meet the nuanced demands of academic information seeking.

2 Related Works

2.1 Academic Information Searching: Cognitive Process to Cognitive Load

Academic information searching is a cognitively demanding activity that requires users to engage in higher-order processes such as comprehension, evaluation, and synthesis. Unlike routine tasks, academic searching involves constructing meaning from fragmented information, integrating diverse perspectives, and aligning search strategies with evolving goals. The process of information searching is a complex cognitive task that involves decision-making, problem-solving, evaluation, and the use of both cognitive and metacognitive strategies [21]. Foundational cognitive information retrieval models emphasize the dynamic interaction between users' mental states and search systems [22][23]. Marchionini's model of exploratory search further illustrates how searching supports learning and investigation, with users continuously interpreting results and adjusting their approach [24]. These models highlight the complexity and active nature of academic search behaviour, underscoring the central role of cognitive processes in shaping outcomes.

To fully understand the mental demands of academic search tasks, one must consider the cognitive processes that underpin human thought and behaviour. These processes—such as attention, memory, reasoning, and problem-solving—are essential for navigating information-rich environments. As Neisser explains, cognition involves the transformation and application of sensory input, enabling humans to make decisions, learn, and adapt across diverse contexts [25]. The APA Dictionary of Psychology echoes this, defining cognitive processes as fundamental mental functions tied to knowledge acquisition and use.

Cognition has been modelled through various theoretical lenses. Early models viewed it as a sequential information-processing system, comprising input, processing, and output stages [26][27]. The Layered Reference Model of the Brain (LRMB) advanced this perspective by mapping 37 cognitive processes across six interconnected layers—from sensation and perception to higher-order thinking and metacognition [28]. This layered model highlights how foundational processes like attention and categorization interact with complex operations such as synthesis and evaluation—exactly the kinds of activities required during academic searching.

Empirical studies further validate the centrality of these processes in professional and academic search contexts. A significant study revealed that nearly half of the cognitive demands in professional knowledge work stem from search and decision-making processes [20]. This insight points to the urgent need for more thoughtfully designed interventions aimed at supporting these foundational activities. Mao et al. reinforce this point by showing that individual cognitive traits, such as need for cognitive closure (NFCC), can significantly shape search behaviour [29]. Their research revealed that users high in NFCC tend to favour quick, structured strategies (e.g., limited keyword variation but broader page exploration), influencing both the efficiency and creativity of outcomes.

These insights lead directly into the concept of cognitive load—the mental effort associated with processing and completing a task. Cognitive Load Theory identifies three types of load: intrinsic, based on task complexity; extraneous, linked to poorly designed environments; and germane, which supports learning and schema development [30]. Cognitive load theory offers insights into how the limitations and capacities of the human information processing system can be applied to optimize instructional design and learning environments [31], particularly in the context of academic searching, where effective management of cognitive resources is essential for navigating, evaluating, and synthesizing complex information. Academic search tasks, which require sustained engagement, strategic decision-making, and synthesis, typically impose a high cognitive load.

To measure this, the NASA Task Load Index (NASA-TLX) remains one of the most widely used tools, assessing workload dimensions such as mental demand, effort, and temporal pressure [32]. Its adaptation to academic search contexts highlights its growing relevance in digital and educational environments [33].

Moreover, the relationship between cognitive processes and load is deeply influenced by prior knowledge, search experience, and tool support. Domain experts, for example, typically experience lower intrinsic load due to efficient filtering and strategy use [11]. Factors like self-efficacy [34], search frequency [35], and technology familiarity [36] also shape how users engage with tasks. Different search goals activate different cognitive strategies [37], while challenges in articulating information needs and source selection—noted in major models by Belkin et al. [38], Wilson [39], and Kuhlthau [1]—further contribute to cognitive strain.

Ultimately, cognitive load is not just a product of task difficulty. It is a dynamic outcome of interacting cognitive operations, individual traits, and system affordances. Investigating how these factors intersect offers a deeper understanding of how academic professionals experience and manage mental effort during information seeking—and how systems can better support them in this process.

2.2 Research Gap and Current Study

Despite significant advancements in digital search technologies and academic information retrieval, much of the existing research continues to focus on generic or simulated tasks, often overlooking the nuanced cognitive processes involved in authentic, real-world academic contexts [21]. While there is extensive literature on cognitive traits—including cognitive learning [40][41], cognitive abilities [42], cognitive styles [43] , and cognitive biases [44][45][46], and cognitive absorption [21]—the underlying, real-time mechanisms that govern expert search behaviour remain underexplored. This disconnect between established cognitive theories and the underexamined realities of in-situ academic search behaviour limits the development of targeted system designs, effective instructional interventions, and theory-driven user models.

Prior research provides useful descriptive accounts of academic information behaviour. Gordon et al. surveyed academic mathematicians and found that challenges such as information overload and limited time hindered effective search practices, despite users' openness to adopting new strategies [47]. Nicholas et al. revealed a strong preference among early career researchers for general tools like Google Scholar, often bypassing library services [48], while Wellings and Casselden highlighted the reliance on familiar tools and networks among engineers and scientists, alongside a lack of awareness about search engine capabilities [49]. These studies contribute valuable insight into preferences and challenges, but they largely focus on observable behaviours, leaving cognitive dimensions unexplored.

Emerging literature has started to address this gap by examining the role of digital literacy and motivational factors. Kose and Kocak found that digital literacy significantly predicts strategic search behaviours in academics, with cognitive absorption mediating this relationship [21]. Their structural model demonstrated that greater daily internet use enhances cognitive absorption, underlining the importance of both skill and immersive engagement. Similarly, Liu et al. explored how task relevance and cognitive load interact to shape decision-making in search contexts [50]. Their findings indicated that while task relevance promotes deeper engagement, its benefits are diminished when users experience cognitive overload—suggesting that engagement is conditional upon the availability of cognitive resources.

Collectively, these studies indicate that academic search behaviour is shaped by a confluence of personal, cognitive, and contextual factors, including digital literacy, motivational relevance, search experience, and cognitive resource availability. However, most continue to isolate variables or rely on controlled environments, limiting ecological validity and leaving a gap in understanding how these elements function dynamically in real-world search contexts.

To address this gap, the present study investigates the cognitive processes that shape academic information seeking, with a focus on how expertise, prior topic knowledge, and perceived tool support influence cognitive workload and user experience. Unlike previous research, this study adopts an ecologically valid approach by capturing both subjective (self-reported) and behavioural data from participants engaged in self-selected academic search tasks. This dual-pronged data collection allows for a richer, more context-sensitive understanding of user behaviour in domain-specific environments.

Specifically, this paper draws on data collected through pre-search and post-search questionnaires to explore the cognitive states, decision-making strategies, and evaluative reflections that bookend the academic search experience. This targeted focus offers insight into how academic professionals cognitively prepare for and reflect on complex search tasks, and how their thinking patterns, background knowledge, and interactions with digital tools shape cognitive effort and user satisfaction. By empirically linking user characteristics and perceptions to distinct dimensions of cognitive load and affective outcomes, this study contributes to a more comprehensive understanding of the mental demands of academic searching. These insights, in turn, support the design of more adaptive digital environments and personalized interventions that align with the authentic cognitive needs of scholarly users.

3 Research Question and Hypotheses

This study investigates the cognitive factors that influence scholarly information seeking, focusing on how users' expertise, search habits, and available support tools shape their perceived mental workload and satisfaction. Grounded in cognitive load theory and models of human information interaction, this work aims to inform the design of cognitive tools that better support complex academic tasks.

Research Question (RQ): How do prior topic knowledge, search experience, and perceived adequacy of search tools relate to cognitive load and satisfaction in academic information searching?

Hypotheses

H1: Higher self-rated topic knowledge will be associated with lower perceived cognitive load, particularly in the dimensions of mental demand, task complexity, and mental fatigue.

According to Cognitive Load Theory [30], individuals with prior knowledge are better equipped to process task-relevant information efficiently, reducing intrinsic cognitive load. In academic search contexts, topic familiarity enables users to recognize relevant concepts more quickly, apply known strategies, and avoid unnecessary cognitive strain. Previous research in instructional and information science domains [11][51] suggests that knowledgeable users allocate cognitive resources more effectively, leading to lower perceptions of mental effort and complexity.

H2: Higher self-rated confidence and perceived search efficiency will be associated with greater satisfaction and lower perceived effort and mental demand during academic search tasks.
User experience models suggest that perceived control and competence are closely linked to positive task evaluations [52]. In academic search, confidence may reflect a user's belief in their ability to navigate complex information environments, while perceived efficiency may influence how mentally taxing the task feels. Although few studies have explicitly tested this link, related work in HCI and UX indicates that users' self-perceptions often shape their satisfaction more than objective task outcomes [53]. This hypothesis tests whether metacognitive appraisal (confidence/efficiency) translates into affective outcomes (satisfaction) and reduced cognitive strain.

H3: Higher perceived adequacy of academic search tools will be associated with lower levels of cognitive load across multiple dimensions (e.g., mental demand, temporal demand, effort), and with greater satisfaction following the search task.
Effective tools can reduce extraneous cognitive load by helping users locate, organize, and synthesize information more efficiently. In contrast, inadequate tools may increase effort by requiring users to compensate with their own strategies [4][13]. While prior research has focused on retrieval success and usability, less is known about how users experience mental demand, time pressure, or fatigue when tools are perceived as insufficient. This hypothesis tests whether perceived tool support alleviates cognitive effort and enhances satisfaction—key dimensions of academic search performance and user experience.

H4: Higher perceived mental demand, effort, and frustration will be negatively associated with satisfaction and confidence in the search process.
As cognitive load increases, users may feel overwhelmed or less in control, potentially lowering their confidence and satisfaction with the task [13][32]. However, emerging perspectives also suggest that certain types of cognitive engagement—such as concentration and complexity—may actually enhance satisfaction, especially when the task is intellectually stimulating [17]. This hypothesis explores both the classic assumption that higher load reduces satisfaction, and the possibility that "desirable difficulty" contributes positively to the user experience in scholarly contexts.

3 Methodology

3.1 Research Design

The research project adopts a mixed-methods approach to investigate the cognitive processes underlying academic information searching. By integrating both qualitative and quantitative methods, it aims to capture real-time cognitive activity alongside reflective insights, offering a comprehensive view of expert search behaviours. The study was structured into three distinct phases: pre-task preparation, task execution (search session), and post-task reflection. This structure allowed for layered data collection encompassing both observable behaviours and participants' internal evaluations.

For the scope of this paper, we focus exclusively on data collected through pre-task and post-task questionnaires, which provide a snapshot of participants' cognitive states and perceptions before and after the search session. The analysis of think-aloud protocols and retrospective interviews will be presented in subsequent publications.

3.2 Procedure

The study consisted of three phases: a pre-task questionnaire, a search task, and a post-task questionnaire. For the purposes of this paper, only data from the pre-task and post-task questionnaires, along with search session duration, were analysed.

1. **Pre-Task**

After recruitment through university mailing lists and academic community messenger groups, participants book a schedule for study then began by completing the pre-task questionnaire. This questionnaire gathered information about their academic background, search experience, and preparation for the search task. Participants were asked to provide 1-2 keywords or short phrases related to a topic they were currently researching or interested in exploring, along with a brief description of their research question or information need. They also rated their knowledge about the topic they would be searching for during the session. This preparation helped ensure that participants would engage in authentic search tasks aligned with their genuine research interests. The details of this will be explained in the Data Collection Instruments section.

2. **Task Execution/Search Session**

Prior to beginning the search session, participants were provided with detailed instructions to prepare a distraction-free environment and ensure a stable internet connection. They used their own devices and preferred academic tools. A short video tutorial was shared to explain the think-aloud protocol, enabling participants to verbalize their cognitive processes during the task.

During the search session, participants were asked to retrieve a minimum of 3 relevant academic resources related to their chosen topic while verbalizing their thought processes using the think-aloud method. Although participants had previously submitted 1–2 keywords or short phrases to describe their topic, this input was for documentation purposes only. During the task itself, they were free to use any number or type of queries, terms, or search strategies they deemed appropriate. Participants were given 20 minutes to complete their search task, with an additional 10-minute buffer if needed. They were instructed to share their screens, which showed their entire information searching process, including any additional applications they might use (e.g., PDF readers, reference managers). The sessions were conducted online via Zoom, where participants shared their screens and audio for recording. The researcher observed the process but minimized interference to avoid disrupting the natural search behaviour.

3. **Post-Task**

Immediately following the search task, participants completed the post-task questionnaire. The post-task questionnaire was designed to explore both cognitive workload and search experience, capturing how participants evaluated their task engagement, perceived success, and tool interaction. It consisted of two main components: cognitive load dimensions and user experience reflections. The details of this will be explained in Data Collection Instruments section.

Following the post-task questionnaire, participants engaged in a 30-minute retrospective interview to discuss their search experience in greater depth. Overall, the full study session—including all three phases—lasted approximately 60 to 90 minutes and generated a rich dataset comprising screen and audio recordings, researcher observations, and questionnaires and interview responses.

3.3 Ethics and Data Management

The study was approved by the Management School University of Sheffield Ethics Review Procedure and complied with UK GDPR regulations. Participants provided informed consent and were assured of their right to withdraw at any point during the study. No incentives were given to participants. All data were anonymized and securely stored, with anonymized datasets deposited in the university's ORDA repository for future research.

3.4 Data Collection Instruments

The pre-task questionnaire used in this study captures several aspects of pre-search planning, including academic background, search experience, and preparation for the search task. Questions about search frequency, types of searches performed, and typical starting points provide insights into participants' search habits and strategies. Similarly, questions about self-rated knowledge and confidence in searching skills reveal metacognitive aspects of pre-search planning.

The questionnaire primarily employed 5-point Likert scales to measure participants' self-assessments and behaviours. For example, confidence in information searching skills was measured on a 5-point scale ranging from "Not confident at all" to "Extremely confident," while knowledge about the search topic used a scale from "Not knowledgeable at all" to "Extremely knowledgeable." This 5-point structure was selected because it offers a balanced range of options with a neutral midpoint, allowing participants to express nuanced opinions rather than forcing a binary choice [54]. Each section of the pre-task questionnaire was grounded in relevant literature, as shown in Table 1.

Table 1: Mapping of Pre-Task Questionnaire Items to Supporting Literature

Section	Question	Supporting Literature
Academic Profile	Academic role, education, field, experience	Understanding user expertise and background is foundational for contextualizing information-seeking behaviour [37]
Search Experience	Search frequency and time spent	Frequency and intensity of searching are core variables in information behaviour studies [35]
Search Experience	Types of searches (lookup, exploratory, etc.)	Different search types require different cognitive strategies [37]
Search Experience	Information source preferences	Source selection reflects users' information needs and search strategies [39]
Search Habits	Starting point for search	Initial search behaviour is a key stage in models such as Kuhlthau's ISP [1]
Search Habits	Confidence in searching skills	Self-efficacy influences search strategy and persistence [34]
Search Habits	Device and tool usage	Technology adoption and tool use are critical in modern information seeking [36]
Task Preparation	Keywords and information need articulation	Articulating information needs is a central step in all major search models [38]
Task Preparation	Prior knowledge of topic	Prior knowledge shapes search strategies and evaluation [11]

The post-task questionnaire was divided into two main sections:

1. **Cognitive Load Dimensions**

Cognitive load was assessed using a modified version of the NASA Task Load Index (NASA-TLX) [32], adapted to reflect the specific cognitive demands of academic search tasks. While the original NASA-TLX includes six dimensions—mental demand, physical demand, temporal demand, performance, effort, and frustration—this study focused on the cognitive aspects most relevant to information seeking. Physical demand and frustration were excluded, and additional dimensions were incorporated to capture higher-order cognitive processes, including task complexity, concentration, information processing, strategy development, and mental fatigue. These extensions are grounded in cognitive load theory [30][55] and have been validated in educational and search-related contexts. Participants rated each dimension using a 5-point Likert scale ranging from "Strongly disagree" to "Strongly agree."

Post-search reflection encompasses the cognitive processes of evaluation, integration, and meaning making. After completing a search, individuals assess the relevance and utility of the information they have found, integrate it with their existing knowledge, and determine whether their information needs have been satisfied. These reflective processes are critical for learning and knowledge construction.

2. **Search Experience Measures**

The second part captured participants' reflections on:

a. Satisfaction with search results (from "Extremely dissatisfied" to "Extremely satisfied")
b. Confidence in finding relevant information (from "Not confident at all" to "Extremely confident")
c. Perceived efficiency of the search process (from "Not at all" to "Extremely efficient")
d. Reliance on prior knowledge (from "None at all" to "A great deal")
e. Adequacy of current search tools (from "Extremely inadequate" to "Extremely adequate")

Each item in the post-task questionnaire was aligned with established constructs in the literature, as detailed in Table 2.

Table 2: Mapping of Post-Task Questionnaire Items to Supporting Literature

Section	Question	Supporting Literature
Cognitive Load	The tasks were mentally demanding	NASA-TLX validated instrument for assessing perceived mental demand [32]
Cognitive Load	I had to work hard to accomplish my level of performance	The "Effort" dimension in NASA-TLX [32][56]
Cognitive Load	I felt rushed or hurried when performing the tasks	"Temporal Demand" in NASA-TLX [32][57]
Cognitive Load	The tasks were complex and challenging	Task complexity contributes to intrinsic cognitive load [30][58]
Cognitive Load	The tasks required a high degree of concentration	Concentration is closely related to mental demand [32]
Cognitive Load	I had to process a lot of information to complete the tasks	Central to cognitive load theory [30][58]
Cognitive Load	I had to develop new strategies or approaches	Strategy use reflects germane cognitive load [55]
Cognitive Load	I felt mentally tired after completing the tasks	Mental fatigue is a consequence of high cognitive load [55]
Search Experience	Satisfaction with results	User satisfaction as a key IR evaluation metric [59]
Search Experience	Confidence in finding relevant information	Confidence in information seeking [60]
Search Experience	Perceived efficiency	Efficiency in usability evaluation [61]
Search Experience	Reliance on prior knowledge	Prior knowledge and perceived cognitive load [62]

Both questionnaires were administered online, with the pre-task questionnaire completed before the search session and the post-task questionnaire immediately after the search session. This timing ensured that participants' reflections on their search experience were fresh and accurate.

4 Results

4.1 Participant Demographics

The study included 31 participants from UK-based universities, representing diverse academic roles and levels of experience. Participants' roles were categorized into doctoral researchers (39%), early-stage academics (25%), lecturers (16%), and individuals with combined roles such as researcher/lecturer/doctoral researcher (16%). Most participants held a Master's degree (65%), while the remainder had Doctoral degrees.

Participants represented a range of academic disciplines, including STEM (48%), social sciences (32%), and arts and humanities (20%). Prominent fields included engineering, business studies, and psychology. Professional experience varied, with 58% of participants reporting over six years in their field, while 26% had three to six years of experience. This diversity provided a robust foundation for examining the cognitive processes involved in academic information searching.

4.2 Hypotheses

H1: Topic Knowledge and Cognitive Load

To assess whether prior topic knowledge reduced perceived cognitive load, Spearman correlations were conducted between self-rated topic knowledge and each NASA-TLX dimension. Specifically, higher self-rated topic knowledge was associated with lower levels of mental demand ($\rho = -0.406$, $p = 0.0236$) and reduced need for strategy development ($\rho = -0.399$, $p = 0.026$), suggesting that participants who were more familiar with their research topic found the task less mentally taxing and required fewer adaptive strategies. While other dimensions—such as effort ($\rho = -0.329$, $p = 0.0704$) and temporal demand ($\rho = -0.234$, $p = 0.2056$)—also showed negative trends, these did not reach statistical significance.

Similarly, weak and non-significant correlations were observed for mental fatigue, task complexity, concentration, and information processing, indicating that topic familiarity had a limited effect on these aspects of cognitive load (see Fig.1). Overall, the findings partially support the hypothesis, highlighting mental demand and strategy development as key areas where topic knowledge enhances cognitive efficiency.

H2: Self-Rated Search Experience and Subjective Outcomes

Given that search duration was procedurally constrained (20–30 minutes) and all participants successfully retrieved at least three academic sources as instructed, task performance was effectively standardised across the sample.

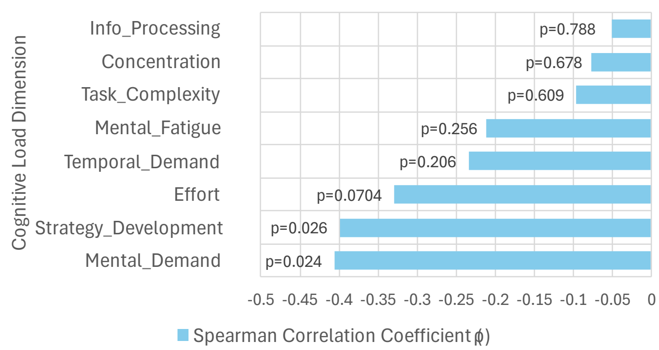

Figure 1: Correlation Between Topic Knowledge and Cognitive Load Dimensions (H1)

Consequently, search time was not used as a behavioural measure of efficiency. Instead, the analysis focused on self-rated confidence and perceived efficiency. Spearman correlation analyses between these self-ratings and outcome variables—mental demand, effort, and satisfaction—revealed no statistically significant relationships.

The strongest observed trend was a weak positive association between perceived efficiency and satisfaction ($\rho = 0.182$, $p = 0.337$), which did not reach significance. Overall, these findings indicate that subjective impressions of search confidence or efficiency do not reliably predict satisfaction or perceived cognitive burden, offering no support for Hypothesis 2 (H2).

H3: Tool Adequacy and Cognitive Load/Satisfaction

To evaluate whether perceived tool adequacy was associated with cognitive burden and user satisfaction, Spearman correlations were conducted between tool adequacy ratings and all dimensions of cognitive load, as measured by the modified NASA-TLX, along with post-task satisfaction. The analysis revealed significant negative correlations between tool adequacy and both mental demand ($\rho = -0.523$, $p = 0.0025$) and temporal demand ($\rho = -0.561$, $p = 0.0010$), indicating that participants who rated their tools as more adequate experienced substantially lower levels of mental strain and time pressure during the academic search task. A moderate, non-significant negative trend was also observed for effort ($\rho = -0.315$, $p = 0.0841$).

No significant associations emerged between tool adequacy and the remaining cognitive load dimensions, such as concentration or task complexity, nor with overall user satisfaction. These findings partially support Hypothesis 3 (H3) and suggest that tool adequacy plays an important role in reducing key aspects of cognitive load, particularly those related to mental effort and time constraints, in academic search contexts.

H4: Cognitive Load Dimensions Predicting Satisfaction and Confidence

To examine whether specific cognitive load dimensions predict user experience, Spearman correlations were computed between NASA-TLX scores and post-task satisfaction and confidence. Two dimensions—task complexity ($\rho = 0.379$, $p = 0.039$) and concentration ($\rho = 0.412$, $p = 0.024$)—were positively associated with satisfaction, suggesting that users found the task more rewarding when it was mentally engaging and required sustained focus. In contrast, no significant correlations were found between any load dimensions and confidence, indicating that confidence may reflect factors beyond immediate cognitive effort, such as prior experience or self-perception (see Fig.2). These results partially support H4, highlighting that user satisfaction in academic search is driven more by cognitive engagement than by ease or simplicity. Table 3 provides a summary of the results for the hypotheses.

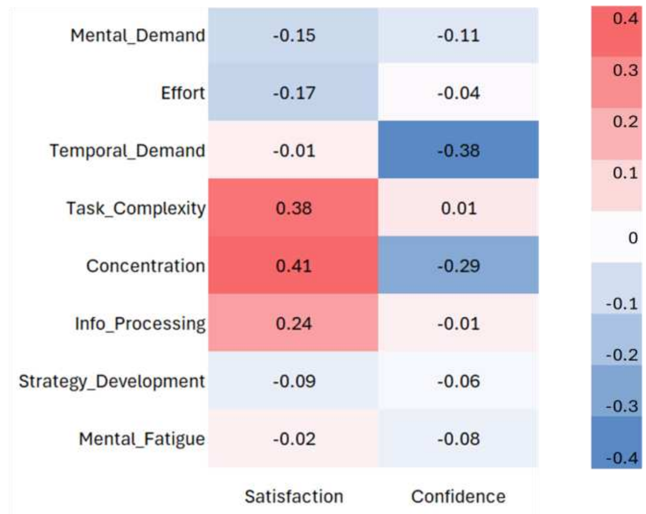

Figure 2: Correlation Between Cognitive Load Dimensions vs Satisfaction & Confidence (H4)

Table 3: Summary of Hypotheses

H	Tested Relationship	Key Finding	Support
H1	Topic Knowledge ⟶ Cognitive Load	Significant negative correlation with Mental Demand	Partially Supported
H2	Confidence & Efficiency ⟶ Satisfaction, Effort, Mental Demand	No significant correlations	Not Supported
H3	Tool Adequacy ⟶ Cognitive Load & Satisfaction	Significant negative correlations with Mental and Temporal Demand; no effect on Satisfaction	Partially Supported
H4	Cognitive Load ⟶ Satisfaction/Confidence	Satisfaction positively associated with Task Complexity and Concentration	Partially Supported

4 Discussions

Prior Knowledge Matters

The findings offer strong support for Cognitive Load Theory [30] and Hypothesis 1 (H1). Participants with higher topic knowledge experienced significantly lower mental demand, suggesting that domain familiarity reduces intrinsic cognitive load by enabling more efficient information filtering and strategy use [11][51]. This confirms the critical role of prior knowledge in shaping the cognitive dynamics of search, particularly in complex academic tasks.

The relevance of prior knowledge was also evident in the pre-task phase, where participants articulated their research topic and search goals. This aligns with Belkin et al.'s ASK model [38] and Wilson's problem-solving model [39], which both underscore the cognitive demands involved in articulating information needs. Furthermore, as Wildemuth notes, prior knowledge not only reduces load but also improves evaluation and synthesis—core activities in academic information seeking [11].

The Confidence Disconnect

The findings related to Hypothesis 2 (H2) challenge established UX and information behaviour assumptions. While Norman [52] and Makri et al. [53] suggest that confidence and perceived efficiency are strong predictors of satisfaction and reduced workload, no significant relationships were observed between these variables and satisfaction, effort, or mental demand in this study. This supports the work of Kelly et al. [17][61], who cautioned that confidence may diverge from actual cognitive performance, especially in tasks characterized by ambiguity and evolving user needs.

Academic searching is a cognitively rich activity that often lacks clearly defined success metrics. Users may feel confident because of interface familiarity or initial progress, even while experiencing high mental demand. These findings suggest that self-perception alone is not a reliable predictor of cognitive or affective outcomes in complex search environments, highlighting the need for multidimensional evaluation frameworks that combine self-report, behavioural, and system-logged data.

Expanding the Role of Tool Support

Hypothesis 3 (H3) was partially supported by the data. Participants who perceived their search tools as adequate reported significantly lower mental and temporal demand, indicating that system support plays a critical role in alleviating cognitive burden. These findings align with Gwizdka [13] and extend usability research by demonstrating that tool adequacy influences not only task efficiency, but also users' subjective experiences of effort and time pressure. However, no significant association was found between perceived tool adequacy and post-task satisfaction, suggesting that while tools can reduce cognitive strain, they may not directly influence users' overall evaluative judgments of the search experience.

The post-task measure of tool adequacy was informed by established usability research on perceived system support [63]. Unlike studies that focus solely on interface design or retrieval performance, the present study highlights that users' perceptions of tool support—or its absence—can meaningfully impact cognitive workload during academic search tasks. These findings also resonate with recent calls to map user-perceived tool limitations to specific cognitive challenges (e.g., information overload, synthesis complexity), thereby providing a foundation for the development of cognitively aware systems that better support research-oriented tasks.

Satisfaction Beyond Simplicity

Findings from Hypothesis 4 (H4) reveal that satisfaction was not driven by ease or reduced effort, but rather by task complexity and concentration—dimensions often associated with germane cognitive load [55]. This supports the concept of desirable difficulty [64], where meaningful cognitive effort leads to deeper engagement and positive affective responses. In academic search, users appear to value intellectually stimulating tasks, provided they can remain focused and mentally immersed. These results support the broader use of the NASA-TLX beyond traditional usability testing [32][55], as it captures not only strain but also cognitive engagement. It also connects to Saracevic's argument that user satisfaction is complex and multi-layered, influenced by relevance, task success, and cognitive control [59].

Toward a Cognitive Model of Academic Search

These findings align with broader cognitive models of search and knowledge work. As Niwanputri et al. observed, searching and decision-making comprise nearly half of cognitive activity in professional settings, reinforcing the need to understand how users think while searching, not just what they click [20]. Additionally, emerging work on individual cognitive traits, such as Need for Cognitive Closure [29], suggests that cognitive effort and tool perception may vary based on psychological factors—offering a future avenue for expanding the current study's model. By focusing on authentic academic search behaviour and assessing both cognitive load and affective responses, this study extends the body of work on cognitive processes in knowledge work [14][20]. It highlights that users do not simply need faster or more efficient tools—they need systems that understand and support their cognitive processes. This shift from usability toward cognitive augmentation is essential for the next generation of knowledge work technologies.

5 Conclusion

This study explored the cognitive and experiential dimensions of academic information searching, examining how topic knowledge, perceived tool adequacy, and self-assessed search experience influence cognitive load, satisfaction, and confidence. By engaging participants in authentic, self-directed academic search tasks and capturing both cognitive and affective responses, the study provides a deeper understanding of how real-world search behaviour unfolds in knowledge work. Key findings showed that topic knowledge significantly reduced mental demand, supporting Cognitive Load Theory and reinforcing the value of domain familiarity in reducing intrinsic cognitive load. Tool adequacy also played a critical role, with higher perceived support associated with significantly lower mental and temporal demand, though it did not significantly predict satisfaction. Notably, self-rated confidence and efficiency were not reliable predictors of cognitive experience, challenging assumptions in existing user experience models. Importantly, satisfaction was more closely linked to cognitive engagement—specifically task complexity and concentration—rather than ease or simplicity. These insights suggest that academic users benefit not only from usable interfaces, but from systems that actively support strategic thinking, focus, and deeper mental processing. As such, the study points toward a shift from designing for usability alone to developing cognitively supportive systems that augment engagement and decision-making in knowledge work.

Nevertheless, the study has several limitations. The small sample size (N = 31) limits generalizability, and reliance on self-report data may not fully capture real-time cognitive processes. The structured task design, while useful for comparison, may not reflect the nonlinear and iterative nature of academic search in practice. Furthermore, individual cognitive traits—such as digital literacy, need for cognitive closure, or cognitive flexibility—were not assessed, yet likely shape how users experience search complexity and evaluate tool support.

These preliminary findings offer valuable insights into the bookends of academic search behaviour—namely the cognitive states before and after task execution—laying the groundwork for deeper analysis of in-task cognitive dynamics in future work. Subsequent phases of this study will focus on analysing the think-aloud protocols and retrospective interviews, offering a more granular understanding of the strategies, challenges, and decision-making processes that unfold during real-time academic search.

In addition, future research will aim to map the identified cognitive processes involved in academic information searching with the available supporting tools. This mapping will allow us to identify gaps where certain cognitive functions remain unsupported by current systems. These unmet needs will then serve as a baseline for defining system requirements, ultimately guiding the development of new tools or the enhancement of existing ones to better support complex academic tasks. Ultimately, this study reinforces a growing shift in information science and human-computer interaction: from building faster or simpler tools to designing systems that actively support cognitive engagement. As knowledge work becomes increasingly complex, the future of academic search lies not only in retrieving information—but in supporting how researchers think, strategize, and synthesize throughout the process.

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References

[1] Carol C. Kuhlthau. 1991. Inside the search process: Information seeking from the user's perspective. *Journal of the American Society for Information Science* 42, 5 (1991), 361–371. https://doi.org/10.1002/(SICI)1097-4571(199106)42:5%3C361::AID-ASI6%3E3.0.CO;2-%23

[2] Nicholas J. Belkin. 1980. Anomalous states of knowledge as a basis for information retrieval. *Canadian Journal of Information Science* 5, 1 (1980), 133–143.

[3] Soo Young Rieh and Hong Iris Xie. 2006. Analysis of multiple query reformulations on the web: The interactive information retrieval context. *Information Processing & Management* 42, 3 (2006), 751–768. https://doi.org/10.1016/j.ipm.2005.05.005

[4] Orland Hoeber, Dolinkumar Patel, and Dale Storie. 2019. A Study of Academic Search Scenarios and Information Seeking Behaviour. *In Proceedings of the 2019 Conference on Human Information Interaction and Retrieval (CHIIR '19).* Association for Computing Machinery, New York, NY, USA, 231–235. https://doi.org/10.1145/3295750.3298943

[5] Orland Hoeber and Dale Storie. 2022. Information seeking within academic digital libraries: a survey of graduate student search strategies. *In Proceedings of the 22nd ACM/IEEE Joint Conference on Digital Libraries (JCDL '22).* Association for Computing Machinery, New York, NY, USA, Article 25, 1–5. https://doi.org/10.1145/3529372.3533286

[6] Sergey Brin and Lawrence Page. 2012. Reprint of: The anatomy of a large-scale hypertextual web search engine. *Computer Networks* 56, 18 (2012), 3825–3833. https://doi.org/10.1016/j.comnet.2012.10.007

[7] Bernard J. Jansen, Amanda Spink, and Tefko Saracevic. 2000. Real life, real users, and real needs: a study and analysis of user queries on the web. *Information Processing & Management* 36, 2 (2000), 207–227. https://doi.org/10.1016/S0306-4573(99)00056-4

[8] Hong Iris Xie and Soohyung Joo. 2010. Transitions in search tactics during the Web-based search process. *Journal of the American Society for Information Science and Technology* 61, 11 (2010), 2188–2205. https://doi.org/10.1002/asi.21391

[9] Susan Knight and Janice Burn. 2005. Developing a framework for assessing information quality on the World Wide Web. *Informing Science Journal* 8 (2005), 159–172. https://doi.org/10.28945/493

[10] Diana Tabatabai and Bruce M. Shore. 2005. How experts and novices search the Web. *Library & Information Science Research* 27, 2 (2005), 222–248. https://doi.org/10.1016/j.lisr.2005.01.005

[11] Barbara M. Wildemuth. 2004. The effects of domain knowledge on search tactic formulation. *Journal of the American Society for Information Science and Technology* 55, 3 (2004), 246–258. https://doi.org/10.1002/asi.10367

[12] Nancy Nelson Spivey. 1996. *The Constructivist Metaphor: Reading, Writing, and the Making of Meaning.* Brill.

[13] Jacek Gwizdka. 2010. Distribution of cognitive load in Web search. *Journal of the American Society for Information Science and Technology* 61, 11 (2010), 2167–2187. https://doi.org/10.1002/asi.21385

[14] Ann-Kathrin Kunz, Olga Zlatkin-Troitschanskaia, Susanne Schmidt, Marie-Theres Nagel, and Sebastian Brückner. 2024. Investigation of students' use of online information in higher education using eye tracking. *Smart Learn. Environ.* 11, 44 (2024). https://doi.org/10.1186/s40561-024-00333-6

[15] Taraneh Khazaei and O. Hoeber. 2017. "Supporting academic search tasks through citation visualization and exploration." *International Journal on Digital Libraries*, 18 (2017): 59-72. https://doi.org/10.1007/s00799-016-0170-x.

[16] Catherine Chavula, Yujin Choi, and Soo Young Rieh. 2023. SearchIdea: An Idea Generation Tool to Support Creativity in Academic Search. In Proceedings of the 2023 Conference on Human Information Interaction and Retrieval (CHIIR '23). Association for Computing Machinery, New York, NY, USA, 161–171. https://doi.org/10.1145/3576840.3578294

[17] Diane Kelly, Jaime Arguello, Ashlee Edwards, and Wan-ching Wu. 2015. Development and Evaluation of Search Tasks for IIR Experiments using a Cognitive Complexity Framework. *In Proceedings of the 2015 International Conference on The Theory of Information Retrieval (ICTIR '15).* Association for Computing Machinery, New York, NY, USA, 101–110. https://doi.org/10.1145/2808194.2809465

[18] Zhao Liu, Xuyan Wang, and Lei Li. 2025. ChatGPT-Assisted Information Retrieval: A Comparative Study of User Behavior in Academic Information Retrieval. *Proceedings of the 24th ACM/IEEE Joint Conference on Digital Libraries.* Association for Computing Machinery, New York, NY, USA, Article 88, 1–3. https://doi.org/10.1145/3677389.3702595

[19] Orland Hoeber and Dale Storie. 2022. Information seeking within academic digital libraries: a survey of graduate student search strategies. *In Proceedings of the 22nd ACM/IEEE Joint Conference on Digital Libraries (JCDL '22).* Association for Computing Machinery, New York, NY, USA, Article 25, 1–5. https://doi.org/10.1145/3529372.3533286

[20] Ginar S. Niwanputri, Elaine G. Toms, and Andrew Simpson. 2023. Untangling Cognitive Processes Underlying Knowledge Work. In *CHIIR '23: Proceedings of the 2023 Conference on Human Information Interaction and Retrieval.* ACM, New York, NY, 401–405. https://doi.org/10.1145/3576840.3586162

[21] Betul Tok Kose and Omer Kocak. 2024. The predictors of academics' online information searching strategies: A structural model integrating cognitive absorption and digital literacy. *Library & Information Science Research* 46, 2 (April 2024), 101299. https://doi.org/10.1016/j.lisr.2024.101299

[22] Peter Ingwersen. 1992. *Information Retrieval Interaction.* Taylor Graham, London, UK.

[23] Peter Ingwersen and Kalervo Järvelin. 2005. *The turn: Integration of information seeking and retrieval in context.* Vol. 18. Springer Science & Business Media. Berlin, Germany.

[24] Gary Marchionini. 2006. Exploratory search: from finding to understanding. Commun. ACM 49, 4 (April 2006), 41–46. https://doi.org/10.1145/1121949.1121979

[25] Ulrich Neisser. 1967. *Cognitive Psychology.* Appleton-Century-Crofts, New York, US.

[26] Donald E. Broadbent. 1958. *Perception and Communication.* Pergamon Press, Oxford, UK.

[27] Dominic W. Massaro and Nelson Cowan. 1993. Information processing models: microscopes of the mind. *Annual Review of Psychology* 44, 1 (1993), 383–425. https://doi.org/10.1146/annurev.ps.44.020193.002123

[28] Yingxu Wang, Ying Wang, Shushma Patel, and Dilip Patel. 2006. A layered reference model of the brain (LRMB). *IEEE Transactions on Systems, Man, and Cybernetics, Part C* 36, 2 (2006), 124–133. https://doi.org/10.1109/TSMCC.2006.871126

[29] Shibo Mao, Di Wang, Chaoying Tang, and Pinhua Dong. 2022. Students' Online Information Searching Strategies and Their Creative Question Generation: The Moderating Effect of Their Need for Cognitive Closure. *Frontiers in Psychology* 13, (May 2022). https://doi.org/10.3389/fpsyg.2022.877061

[30] John Sweller. 1988. Cognitive Load During Problem Solving: Effects on Learning. *Cognitive Science* 12, 2 (April 1988), 257–285. https://doi.org/10.1207/s15516709cog1202_4

[31] Kim Ouwehand, Florence Lespiau, André Tricot, and Fred Paas. 2025. Cognitive Load Theory: Emerging Trends and Innovations. *Education Sciences* 15, no. 4: 458. https://doi.org/10.3390/educsci15040458

[32] Sandra G. Hart and Lowell E. Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in Psychology,* 52 (1988), 139–183. https://doi.org/10.1016/S0166-4115(08)62386-9

[33] Alexander Skulmowski & Kate Man Xu. 2022. Understanding Cognitive Load in Digital and Online Learning: a New Perspective on Extraneous Cognitive Load. *Educ Psychol Rev* 34, 171–196. https://doi.org/10.1007/s10648-021-09624-7

[34] Albert Bandura. 1997. *Self-Efficacy in Changing Societies.* Cambridge University Press. Cambridge, UK.

[35] Donald O. Case and Lisa M. Given. 2016. Looking for Information. Emerald Group Publishing. Leeds, UK.

[36] Pertti Vakkari. 2003. Task-based information searching. *Annual Review of Information Science and Technology* 37, 1 (January 2003), 413–464. https://doi.org/10.1002/aris.1440370110

[37] Gary Marchionini. 1995. Information Seeking in Electronic Environments. Cambridge University Press. Cambridge, UK.

[38] N.J. Belkin, R.N. Oddy, And H.M. Brooks. 1982. Ask For Information Retrieval: Part I. Background And Theory. *Journal of Documentation* 38, 2 (February 1982), 61–71. DOI:https://doi.org/10.1108/eb026722

[39] T.D. Wilson. 1999. Models in information behaviour research. *Journal of Documentation* 55, 3 (August 1999), 249–270. https://doi.org/10.1108/eum0000000007145

[40] Bernard J. Jansen, Danielle Booth, and Brian Smith. 2009. Using the taxonomy of cognitive learning to model online searching. *Information Processing & Management* 45, 6 (November 2009), 643–663. https://doi.org/10.1016/j.ipm.2009.05.004

[41] Rishita Kalyani and Ujwal Gadiraju. 2019. Understanding User Search Behavior Across Varying Cognitive Levels. In *Proceedings of the 30th ACM Conference on Hypertext and Social Media (HT '19).* Association for Computing Machinery, New York, NY, USA, 123–132. https://doi.org/10.1145/3342220.3343643

[42] S. J. Westerman and T. Cribbin. 2000. Cognitive ability and information retrieval: When less is more. *Virtual Reality* 5, 1 (March 2000), 1–7. https://doi.org/10.1007/bf01418971

[43] Khamsum Kinley, Dian Tjondronegoro, Helen Partridge, and Sylvia Edwards. 2014. Modeling users' web search behavior and their cognitive styles. *Journal of the Association for Information Science and Technology* 65, 6 (January 2014), 1107–1123. https://doi.org/10.1002/asi.23053

[44] Ben Wang and Jiqun Liu. 2024. Cognitively Biased Users Interacting with Algorithmically Biased Results in Whole-Session Search on Debated Topics. *In Proceedings of the 2024 ACM SIGIR International Conference on Theory of Information Retrieval (ICTIR '24).* Association for Computing Machinery, New York, NY, USA, 227–237. https://doi.org/10.1145/3664190.3672520

[45] Leif Azzopardi. 2021. Cognitive Biases in Search: A Review and Reflection of Cognitive Biases in Information Retrieval. *In Proceedings of the 2021 Conference on Human Information Interaction and Retrieval (CHIIR '21).* Association for Computing Machinery, New York, NY, USA, 27–37. https://doi.org/10.1145/3406522.3446023

[46] Leif Azzopardi and Jiqun Liu. 2024. Evaluating Cognitive Biases in Conversational and Generative IIR: A Tutorial. *In Proceedings of the 2024 Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region (SIGIR-AP 2024).* Association for Computing Machinery, New York, NY, USA, 287–290. https://doi.org/10.1145/3673791.3698437

[47] Ian D. Gordon, Brian D. Cameron, Debbie Chaves, and Rebecca Hutchinson. 2020. Information Seeking Behaviors, Attitudes, and Choices of Academic Mathematicians. *Science & Technology Libraries* 39, 3 (2020), 253–280. https://doi.org/10.1080/0194262X.2020.1758284

[48] David Nicholas, Cherifa Boukacem-Zeghmouri, Blanca Rodríguez-Bravo, Jie Xu, Anthony Watkinson, A. Abrizah, Eti Herman, and Marzena Świgoń. 2017. Where and how early career researchers find scholarly information. *Learned Publishing* 30, 1 (January 2017), 19–29. https://doi.org/10.1002/leap.1087

[49] Susan Wellings and Biddy Casselden. 2017. An exploration into the information-seeking behaviours of engineers and scientists. *Journal of Librarianship and Information Science* 51, 3 (November 2017), 789–800. https://doi.org/10.1177/0961000617742466

[50] Xueping Liu, Lingling Ji, and Huamao Peng. 2020. The Impacts of Task Relevance and Cognitive Load on Adults' Decision Information Search. *Aging, Neuropsychology, and Cognition* 28, 1 (2020), 78–96. https://doi.org/10.1080/13825585.2020.1712320

[51] Slava Kalyuga, Paul Ayres, Paul Chandler, and John Sweller. 2003. The Expertise Reversal Effect. *Educational Psychologist* 38, 1 (2003), 23–31. https://doi.org/10.1207/S15326985EP3801_4

[52] Donald A. Norman. 1993. Cognition in the Head and in the World: An Introduction to the Special Issue on Situated Action. Cognitive Science 17, 1 (January 1993), 1–6. https://doi.org/10.1207/s15516709cog1701_1

[53] Stephann Makri, Ann Blandford, Mel Woods, Sarah Sharples, and Deborah Maxwell. 2014. "Making my own luck": Serendipity strategies and how to support them in digital information environments. *Journal of the Association for Information Science and Technology* 65, 11 (March 2014), 2179–2194. https://doi.org/10.1002/asi.23200

[54] Jeff Sauro and Joseph S. Dumas. 2009. Comparison of three one-question, post-task usability questionnaires. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09).* Association for Computing Machinery, New York, NY, USA, 1599–1608. https://doi.org/10.1145/1518701.1518946

[55] Fred Paas, Alexander Renkl, and John Sweller. 2003. Cognitive Load Theory and Instructional Design: Recent Developments. *Educational Psychologist* 38, 1 (2003), 1–4. https://doi.org/10.1207/S15326985EP3801_1

[56] Fred G.W.C. Paas and Jeroen J.G. van Merriënboer. 1994. **Instructional** control of cognitive load in the training of complex cognitive tasks. *Educational Psychology Review* 6 (1994), 351–371. https://doi.org/10.1007/BF02213420

[57] Susana Rubio, Eva Díaz, Jesús Martín, and José M. Puente. 2004. Evaluation of subjective mental workload: A comparison of SWAT, NASA-TLX, and workload profile methods. *Applied Psychology* 53, 1 (2004), 61–86. https://doi.org/10.1111/j.1464-0597.2004.00161.x

[58] Roland Brünken, Jan L. Plass, and Detlev Leutner. 2003. Direct measurement of cognitive load in multimedia learning. *Educational Psychologist* 38, 1 (2003), 53–61. https://doi.org/10.1207/S15326985EP3801_7

[59] Tefko Saracevic. 1995. Evaluation of evaluation in information retrieval. In *Proceedings of the 18th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '95).* Association for Computing Machinery, New York, NY, USA, 138–146. https://doi.org/10.1145/215206.215358

[60] Diane Kelly, Susan Dumais, and Jan O. Pedersen. 2009. Evaluation challenges and directions for information-seeking support systems. *Computer* 42, 3 (2009), 60–66. https://doi.org/10.1109/MC.2009.107

[61] Jakob Nielsen. 1993. *Usability Engineering.* Academic Press, Inc., San Diego, CA, USA.

[62] Tino Endres, Oliver Lovell, David Morkunas, Werner Rieß, and Alexander Renkl. 2023. Can prior knowledge increase task complexity? – Cases in which higher prior knowledge leads to higher intrinsic cognitive load. *British Journal of Educational Psychology* 93 (2023), 305–317. https://doi.org/10.1111/bjep.12552

[63] Ann Blandford and Simon Attfield. 2010. The Behaviors: Understanding the "Information Journey". In *Interacting with Information. Synthesis Lectures on Human-Centered Informatics.* Springer, Cham. https://doi.org/10.1007/978-3-031-02189-3_4

[64] Robert A. Bjork and Elizabeth L. Bjork. 2020. Desirable difficulties in theory and practice. *Journal of Applied Research in Memory and Cognition* 9, 4 (2020), 475. https://doi.org/10.1016/j.jarmac.2020.09.003