Cognitive Biases in Search as Learning: Bridging Conceptual Foundations and Empirical Research

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Abstract. *Online search is a key part of how people learn, yet it is not a neutral process. Cognitive biases shape how users search for, select, and interpret information. While the Search as Learning (SAL) field studies how people learn throughout the search process, it has not yet integrated research on cognitive biases. This paper bridges that gap by proposing a conceptual model and an experimental framework that connect SAL with cognitive bias research. We conducted a real-world experiment on confirmation bias, involving learners searching for "The use of AI in education". It showed how prior beliefs influence search behaviors. This work advances both the theoretical understanding and empirical study of biases in SAL, supporting the development of fairer, more transparent, and educationally effective search technologies.*

1. Introduction

The advent of digital technologies and the exponential growth of the Internet have profoundly transformed how individuals seek, access, and engage with information. Search systems have become indispensable tools for knowledge acquisition, and is now deeply intertwined with learning processes [Haider and Sundin, 2019].

This transformation led to the emergence of the *Search as Learning* (SAL) field, which recognizes that the Information-Seeking Process (ISP)[1] is not merely an information retrieval task but a learning process, where effective searching enhances learning outcomes and learning equips individuals with skills for efficient searching [Rieh et al., 2016, Vakkari, 2016]. This perspective is particularly relevant to Informatics in Education, which investigates how computational systems support teaching and learning.

Although advances in search technologies have improved access to information [Aghaei et al., 2022], they also raise epistemological and educational challenges. Search systems are often mistakenly perceived as neutral gateways to knowledge, but their effectiveness is significantly influenced by their underlying architecture (which is

[1]Information-Seeking is a broader term encompassing the entire process an individual undergoes to satisfy an information need. This process involves recognizing and articulating a need for information, searching for information, and using the information found. On the other hand, Information Searching is more specific and refers to the act of querying a search engine (or other source of information) to locate specific information. Here, both terms is going to be used interchangeably.

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prone to algorithmic, data, and presentation biases) and by the cognitive processes and biases of users [Russo and Russo, 2020]. These factors can distort learning, especially when search is the primary tool for understanding complex topics.

Cognitive biases are systematic "errors" in unconscious mental processes that can affect learners as they navigate vast amounts of data, influencing their ability to formulate queries, select information, and interpret results [Azzopardi, 2021]. This is particularly critical in learning contexts, where biased information processing can reinforce misconceptions, hinder critical thinking, and limit exposure to diverse perspectives [Gomroki et al., 2023]. These are significant obstacles to the development of essential digital literacy skills that are increasingly vital in the information society. Despite that, the dynamics of cognitive biases remains underexplored in SAL research.

This gap leads to two central research problems. First, although SAL emphasizes the educational aspects of searching, there is little to none research examining how cognitive biases can impact learning-oriented search tasks. Most existing studies on cognitive bias focus on simple ad-hoc tasks [Azzopardi, 2021, Machado et al., 2024b], which do not capture the complex cognitive dynamics involved in SAL. Consequently, findings on biases from these contexts cannot be directly generalized to SAL.

Second, empirical research on cognitive biases in ISP lacks methodological standardization. Studies are fragmented, use heterogeneous experimental designs, and often reach contradictory conclusions without systematic explanation [Azzopardi, 2021, Gomroki et al., 2023]. This fragmentation impedes cumulative progress, limits replicability, and hinders efforts to mitigate the negative effects of cognitive biases on learning.

This research addresses these problems through two main objectives. The first is the development of a *conceptual model* that integrates SAL and cognitive biases, offering a structured vocabulary and model to guide research and practice. The second is the creation of an *application-level framework* to support standardized, end-to-end empirical experimentation on cognitive biases in SAL. This framework aims to enable reproducible and extensible studies that advance understanding and inform the design of bias-aware educational search systems.

To validate the proposed approach, we implemented an information system grounded in the application framework and conducted an empirical study on *confirmation bias*. The experiment involved 84 participants engaged in a SAL task on "Artificial Intelligence (AI) in education", comparing the behaviors of learners with pre-existing attitudes against those with neutral stances. This investigation, to the best of our knowledge, represents the first end-to-end experimental study of cognitive biases in a SAL context.

Our contributions are threefold[2]: (i) a conceptual model bridging cognitive biases and SAL; (ii) an application-level framework supporting empirical research; and (iii) empirical evidence of how confirmation bias shapes learning-oriented search behavior. In addition, technical contributions include the development of an information system for conducting such experiments and the release of a dataset containing search logs from the study. This work advances research in learning technologies by offering theoretical foundations and practical tools to understand the impact of cognitive biases in SAL. It also contributes to education by informing teacher training, critical digital literacy practices,

[2]The framework and all data created in this research were made available openly here: `https://github.com/sal-research-group/xperframe4sal`

and policy efforts toward responsible use of AI and media literacy in learning contexts.

2. Cognitive Biases in Search

Cognitive biases are systematic deviations from rational judgment that often arise from mental shortcuts that humans employ to make decisions more efficiently [Kahneman, 2011, Tversky and Kahneman, 1992]. Cognitive biases are often explained by the *Dual Process Theory* [Kahneman, 2011]. This theory posits that human thinking is mediated by two distinct cognitive systems: an intuitive, automatic system (System I) and a deliberate, analytical system (System II). System I is fast, effortless, and heuristic-driven, enabling individuals to make quick judgments but often at the expense of accuracy. In contrast, System II is slower, more reflective, and demands greater cognitive effort, leading to more reliable but cognitively taxing decisions. Cognitive biases typically arise when System I dominates, particularly in situations of uncertainty or cognitive overload. True rationality depends on the effective coordination between these two systems [Kahneman, 2011].

In the context of information search, cognitive biases significantly influence the way individuals formulate queries, interpret results, and assess the credibility and relevance of information [Azzopardi, 2021, Gluck, 2020]. Users interacting with search systems, especially for learning purposes, are not purely rational agents. Instead, they are susceptible to cognitive shortcuts that can distort their search behavior, information processing, and ultimately, their learning outcomes.

Research in this domain has identified a range of cognitive biases that manifest at different stages of the Information Seeking Process (ISP). A systematic review by Azzopardi [2021] demonstrates that these biases affect not only user interactions with search systems but also the quality and depth of their learning. The authors categorize the existing literature into four groups: (i) literature reviews, (ii) exploratory studies identifying which biases affect search, (iii) empirical studies examining how biases shape search behavior or how interventions influence this process, and (iv) studies focused on debiasing strategies. Despite growing interest, most research tends to focus on isolated stages of the search process—particularly the judgment stage—rather than on how biases accumulate and interact throughout the entire search journey [Machado et al., 2024a].

Among the most frequently studied biases in search are confirmation bias, anchoring, order effects, exposure bias, and availability bias. Confirmation bias occurs when individuals preferentially seek, interpret, and recall information that supports their pre-existing beliefs [Knobloch-Westerwick et al., 2015, White and Horvitz, 2015], often leading to one-sided learning that reinforces misconceptions. Anchoring bias arises when early pieces of information disproportionately influence subsequent judgments [Shokouhi et al., 2015]. Order effects occur when users give undue weight to information presented at the beginning (primacy effect) or end (recency effect) of search results lists [Murphy et al., 2006, Rieger et al., 2021].

Furthermore, the design of search interfaces and the algorithms that rank and present information can interact with and amplify human biases. Presentation bias, algorithmic bias, and data bias further shape the information landscape [Baeza-Yates, 2020]. For example, if ranking algorithms systematically prioritize content that aligns with a user's prior beliefs, they may inadvertently reinforce anchoring and confirmation biases.

Despite the relevance of this topic, the field faces persistent challenges. These include a lack of standardization in experimental methodologies, a predominant focus on studying biases in isolation rather than examining their combined effects [Gluck, 2020, Gomroki et al., 2023], and an overreliance on artificial tasks that fail to capture the complexity of real-world search scenarios. Additionally, research examining how cognitive biases impact SAL is scarce. Existing studies often overlook the distinct nature of SAL tasks, which involve more complex cognitive processes that are directly reflected in search behaviors. As a result, the dynamics of cognitive biases within these learning processes remain largely unexplored [Machado et al., 2024a].

3. A Conceptual Model for Cognitive Biases in Search as Learning

The lack of research connecting SAL and the study of cognitive biases in search seems, in part, to result from the limited dialogue between these two fields. Researchers in SAL rarely engage with the literature on cognitive biases, while studies on cognitive biases in information seeking tend to overlook the specific characteristics of learning-oriented searches [Machado et al., 2024a]. This gap limits a more in-depth understanding of how bias affects search-mediated learning processes. In this context, a conceptual model that integrates key concepts from both fields can be a valuable contribution. It may help researchers develop a common vocabulary, identify connections between their approaches, and support the advancement of research in learning technologies.

Our first step in developing this model was to understand how SAL is represented in the literature, ensuring that the integration of cognitive biases aligns with how learning is conceptualized in search contexts.

In [Hansen and Rieh, 2016], the authors provide an overview of SAL based on studies published in a special issue of the *Journal of Information Science*. Their model, in Figure 1, illustrates how searching and learning are deeply interconnected processes that occur simultaneously. It highlights that learning is multifaceted and influenced by several factors, including user goals and tasks, knowledge levels, search outcomes, search situations, individual and group behavior, and social and organizational contexts. A key contribution of this model is the idea that learning encompasses the ISP over time and across different spaces, whether physical, digital, individual, or social. However, it does not explicitly consider how cognitive biases influence this process. In this work, we argue that cognitive biases are among the factors that shape both searching and learning.

Machado et al. [2020] proposed a more structured model based on a systematic review of the literature. The model organizes SAL into three interconnected dimensions: user, interaction, and knowledge. It reinforces that SAL is not just about navigating interfaces or retrieving information but about how learners engage with information systems to construct knowledge over time. This perspective emphasizes how individual characteristics, system features, and knowledge representations interact during a SAL task.

More recently, the *SAL Spaceship Model* proposed by Von Hoyer et al. [2022] extends this perspective by offering a refined and systemic representation of SAL. The model consists of five components: (i) learner context, (ii) learner, (iii) interface, (iv) backend of the search system (including algorithms and retrieval mechanisms), and (v) the collective knowledge space. It provides a clear representation of how technological and psychological factors interact in learning-oriented search. However, like previous models, it does not incorporate the dynamics of cognitive biases.

On the other hand, Azzopardi [2021] offers a comprehensive review on how cognitive biases affect users' behavior during information seeking and retrieval. Drawing

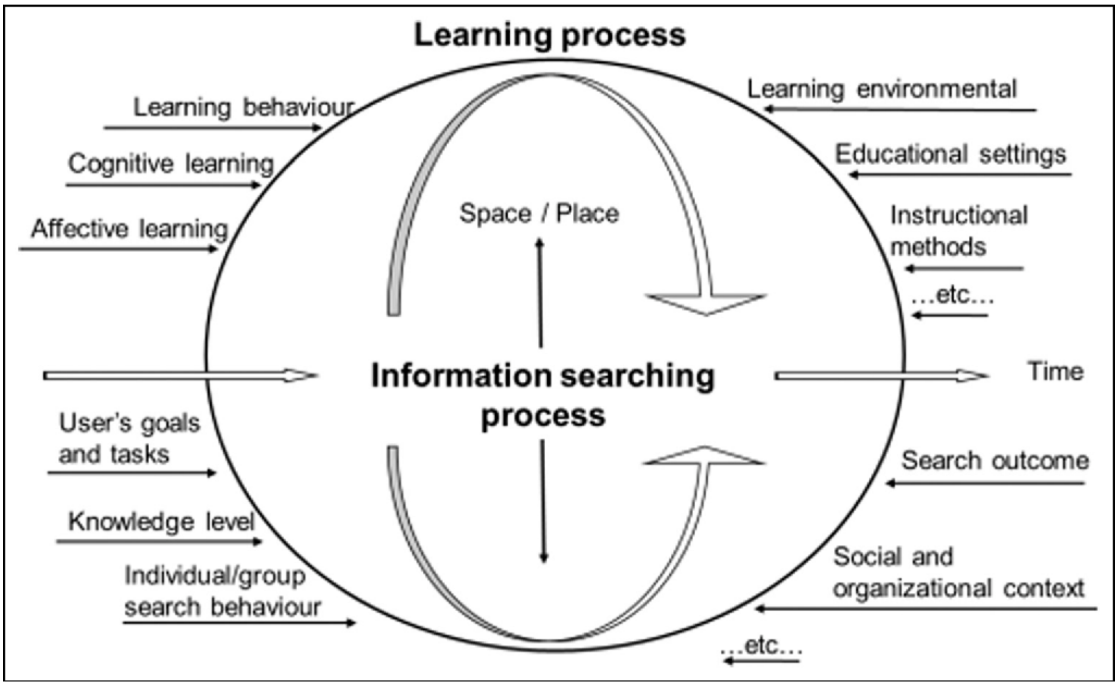

Figure 1. Information searching and learning factors influencing searching as learning. Source: [Hansen and Rieh, 2016].

on over thirty empirical studies, the author demonstrates that biases such as confirmation, anchoring, availability, and exposure systematically influence how users formulate queries, assess information, and make decisions, particularly in high-stakes domains like health and politics. Users tend to seek information that confirms their prior beliefs, rely heavily on the first results presented, and are swayed by the framing and order of information, often leading to distorted judgments and suboptimal decisions. However, most studies reviewed focus on ad-hoc, goal-oriented search tasks aimed at retrieving specific information–very different from the exploratory, open-ended, and cognitively demanding searches typical of SAL. Azzopardi [2021] concludes that understanding these cognitive biases is essential for developing more reliable, ethical, and user-centered information retrieval systems.

Building on insights from both SAL and cognitive biases, we propose the conceptual model shown in Figure 2. The model is divided into two main parts: the user side and the search engine side. This division highlights the distinction between backend mechanisms and learner-centered processes.

On the user side, the central component is the learner, directly engaged in the search process. The learner is influenced by the learner context, which includes factors like prior knowledge, goals, emotions, and others shown in Figure 1 and discussed in [Von Hoyer et al., 2022]. Critically, it also includes *cognitive biases*, which are modeled as part of the learner context. This highlights that biases are not isolated errors but part of the broader set of factors influencing how learners engage with information. They continuously affect how queries are formulated, how results are interpreted, and how information is integrated into knowledge. The learner context operates as a persistent background that shapes perceptions, decisions, and interactions throughout the search and learning process.

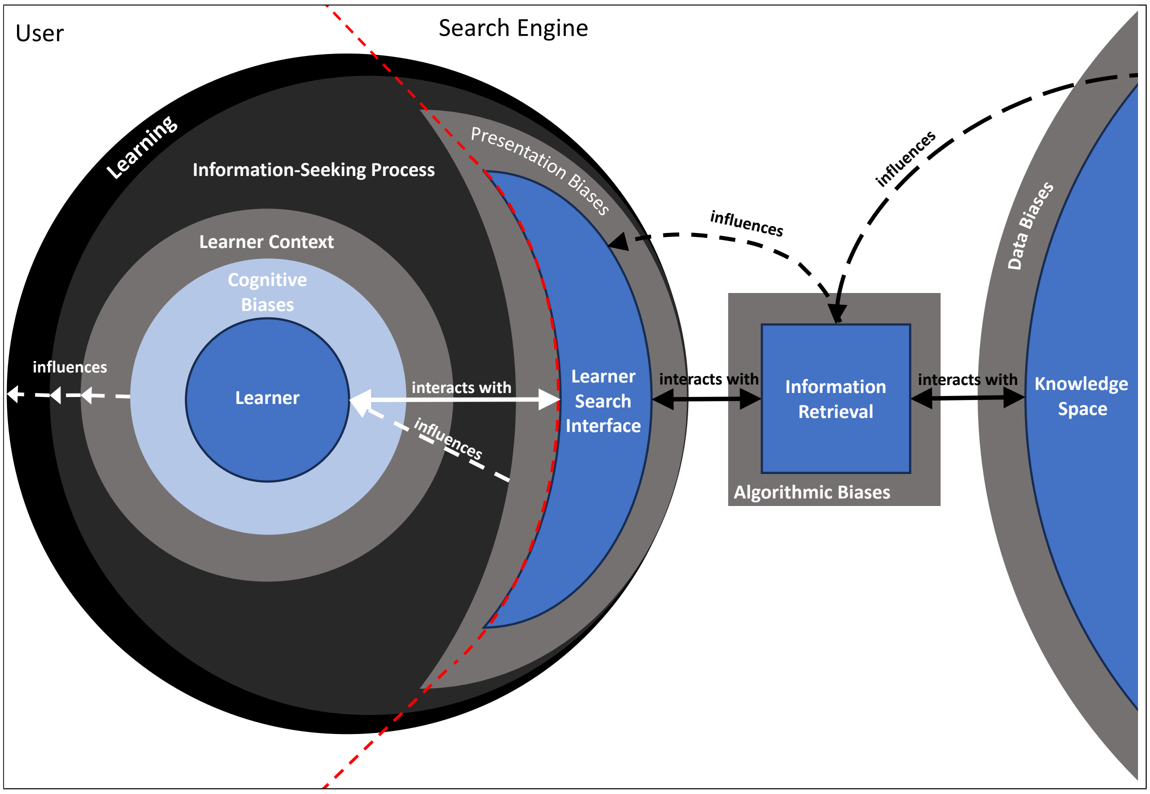

Figure 2. Conceptual model for Cognitive Biases in Search as Learning. Created by the author, inspired by the SAL Spaceship [Von Hoyer et al., 2022].

The leaner search interface acts as the interaction point between the learner and the search system. Following [Hansen and Rieh, 2016], the ISP unfolds within this interaction space, where the learner's cognitive processes are mediated by how the system presents, organizes, and structures information. The interface plays an active role in influencing what learners see first, how they navigate information, and how content is perceived.

On the system side, the search engine backend includes components responsible for indexing, retrieving, ranking, and filtering information. It determines which pieces of the collective knowledge space are made accessible to the learner. Shaped by algorithms, data structures, and retrieval models, the backend defines the information landscape presented to the user. Our model explicitly isolates the backend to emphasize that system-side factors are independent of the user but interact with them through the interface.

Two central processes operate across the model: the ISP and the learning process. The ISP occurs within the boundary between the learner and the interface–this is the interaction space where search actions take place, as discussed by [Machado et al., 2020, Von Hoyer et al., 2022]. The learning process, as described in [Hansen and Rieh, 2016], encompasses the entire model, reinforcing that learning is not something that happens after search but occurs throughout the ISP.

Understanding the dynamics between the components of the model occurs primarily through encompassment relationships. When one component encompasses another, it represents a direct influence, for example, cognitive biases directly influence the learner, and presentation biases directly influence the interface. The model also includes indirect influences, represented by dashed arrows. For instance, while the search engine backend does not interact directly with the learner, it indirectly affects the learner by determining what information is available and how it is ranked, shaping exposure to content and learning outcomes. By following these relationships, it becomes clear that the learning process is influenced not only by the learner's actions but by every element of the system, including backend algorithms, interface design, and the broader knowledge space.

In summary, the conceptual model provides a comprehensive view of how learning, information seeking, and cognitive biases are interconnected. It highlights that cognitive biases are not isolated phenomena, but part of a broader context that interacts with technological components and learning processes. This model offers a foundation for understanding how cognitive biases influence learning-oriented search and supports future research in designing experiments, developing educational technologies, and creating interventions aimed at mitigating the negative impacts of biases in learning through search.

4. A Framework for Empirical Experimentation in Cognitive Biases in Search as Learning

To complement the conceptual model and operationalize its components in empirical research, we developed an application-level framework designed to support the full lifecycle of experiments on cognitive biases in SAL. This framework bridges the gap between conceptual definitions and practical experimentation, providing researchers with the necessary tools to design, execute, and analyze studies in this domain.

The development of this framework was motivated by the observation–discussed in our conceptual analysis–that existing research on cognitive biases in search often lacks standardization. Studies are typically designed in isolation, with varying methodologies, making it difficult to compare results, reproduce experiments, or extend findings–especially in learning-oriented search contexts [Machado et al., 2024a].

4.1. Framework Architecture

The framework architecture is directly inspired by the components and relationships defined in our conceptual model. It is structured to support the two main sides of the model: the *user side* and the *search engine side*, as well as the interaction space between them. The main components of the framework include:

- **Learner Management**: Specializes the user/participant as a learner within the system. It is responsible for storing information that defines the learner's context, including prior knowledge, beliefs, and other relevant factors. This module operationalizes the *Learner Context* from the conceptual model.
- **Search System Environment**: Provides a controlled search interface connected to a search engine backend. This mirrors the *Search Learner Interface* component and its relationship with both the *Learner* and the *Backend* in the conceptual model.
- **Data Logging and Traceability**: Captures detailed logs of learners/system interactions. This layer mirrors the interaction layer, allowing researchers to understand the learners' search behavior. Consequently, the search behavior can be used to measure the influence of some cognitive biases and learning outcomes.
- **Survey and Learning Assessment Tools**: Integrates pre- and post-search questionnaires for measuring learning outcomes, attitude change, satisfaction, and other variables relevant to SAL studies.

- **Experiment Designer**: Allows researchers to define search tasks, assign experimental conditions, configure the availability of pre-search stimuli (e.g., biased materials), and control interface or backend features such as ranking algorithms or result filtering. This reflects the dynamic interplay between user-side factors and system-side parameters.
- **Experiment Management**: It is responsible for importing and exporting experiments. It ensures standardization of experiments in the area, allowing experiments to be easily reproduced and modified in other instances of the system.

4.2. Workflow Support

The framework supports the entire experimental workflow, from participant onboarding to data analysis. A typical workflow includes:

1. Defining the research design (e.g., between-subject, within-subject).
2. Creating tasks aligned with learning-oriented search scenarios.
3. Assigning participants to experimental groups based on learner context (e.g., prior attitudes or knowledge).
4. Monitoring user interaction with the search interface during the task.
5. Collecting data on both search behavior and learning outcomes.
6. Exporting structured datasets for analysis.

4.3. Alignment with the Conceptual Model

A key strength of this application-level framework is its alignment with the conceptual model. The learner is not treated as a passive query generator but as an active agent situated within a rich context—including prior knowledge, goals, and cognitive biases. Likewise, the search engine backend is not a black box but a configurable component whose algorithms, rankings, and data structures can be studied as variables that influence search behavior and learning.

Cognitive biases, represented in the conceptual model as part of the learner context, can be operationalized in the framework by manipulating pre-task stimuli, modifying interface designs, or configuring backend ranking strategies to examine their effects. This design enables the study of both direct and indirect influences within the SAL process, as well as how these influences shape learning outcomes.

4.4. Contribution and Impact

This framework addresses several challenges identified in prior research, including the lack of standardization, limited support for learning-oriented search tasks, and difficulties in reproducing experiments. It enables more rigorous and comparable studies of cognitive biases in SAL by offering:

- A flexible yet structured environment for experiment creation.
- Complete traceability of user behavior and system responses.
- Support for diverse experimental conditions, including attitude manipulation, interface design variations, and backend configurations.
- Integration of learning assessments as a central outcome of search tasks.

Based on the framework architecture, we developed a computational information system that aims to operationalize empirical experiments on cognitive biases in the context of SAL. This was designed to provide comprehensive support for the stages of experimental design, data collection, interaction processing, and analysis, enabling replicable and scalable studies that align with the specific challenges of SAL research.

At a high level, the system can be visualized as having two layers: (i) Application Layer, (ii) Experiment Layer, as represented in Figure 3. Each layer plays a specific role in managing experiments and mediating the interaction between researchers and learners.

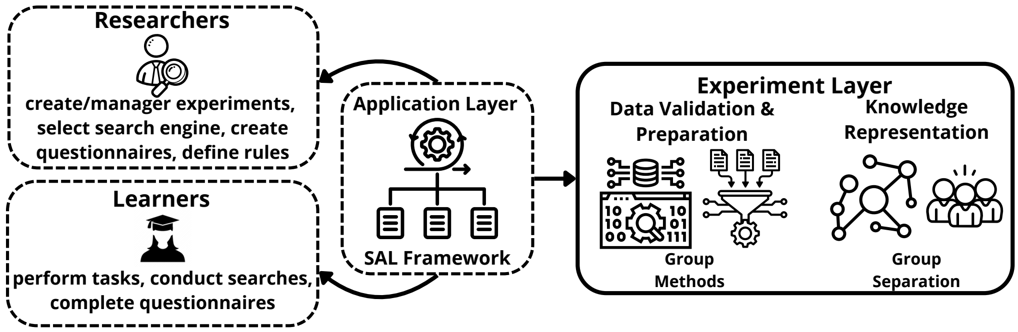

Figure 3. High-Level system architecture: The Application Layer (front-end) mediates user interaction and triggers back-end processes in the Experiment Layer, which is responsible for data validation, experimental logic, and group structuring. Researchers and learners access the system through the Application Layer to either manage or participate in experiments.

The Application Layer corresponds to the interface for interaction with the system's users, both researchers and learners. For researchers, this layer provides tools for managing experiments, defining control variables, creating questionnaires, configuring search engines, and applying group division methods (for example, bias manipulation or forming control groups). For learners, this layer provides the interface for performing search tasks and filling out data collection instruments.

The Experiment Layer is responsible for the operational logic of the experiments. It handles the control of experimental flows, records user interactions (such as queries, clicks, browsing time, and session data), and performs data processing and validation. It also implements group assignment mechanisms, which can be based on random assignment, quasi-experimental designs, or contextual characteristics previously identified in the learners. Within this layer, data is collected and organized in a structured manner to facilitate analysis, generate insights, and support future replication of studies. Additionally, the Experiment Layer manages the databases linked to the search engine used in each experiment, enabling the configuration of different information sources and the assessment of how backend variations influence user behavior.

The actions between the Application Layer and Experiment Layer are logged, allowing analyses of both learner and researcher data. On the one hand, this capability is essential for investigating how cognitive biases manifest themselves in a dynamic and cumulative manner during search tasks focused on knowledge construction, on the other hand, it guarantees provenance over the experiments, allowing easy reproduction and understanding of the data from each experiment, ensuring standardization.

In Section 5, we show how this framework was validated by implementing an experiment focused on studying confirmation bias in the learning context. The results of this experiment demonstrated not only the technical feasibility of the framework, but also its methodological usefulness to support robust investigations into the impacts of cognitive biases in SAL. Therefore, the proposed framework represents a concrete contribution to research in Informatics in Education, offering a methodological and technological infrastructure capable of fostering more rigorous, replicable studies aligned with the specificities of technology-mediated and learning-oriented search processes.

5. Confirmation Bias in Search as Learning: A Study on The Use of Artificial Intelligence in Education

This section summarizes our previously published study described in [Machado et al., 2024b]. The study was designed with two main objectives: (i) to instantiate and validate the application-level framework, and (ii) to investigate how confirmation bias manifests and affects user behavior during exploratory search processes oriented toward learning.

The experiment was carried out within an SAL task focused on the topic of AI in education. This topic was chosen due to its interdisciplinary nature and the diversity of perspectives it offers, allowing for the observation of potential bias dynamics without the high polarization seen in other domains.

The study involved 84 participants. After registering in the system and completing a demographic questionnaire, participants were asked to complete a questionnaire to form a learner context about their stance on the use of AI in education, indicating whether they were for, against, or neutral. Based on the answers, they were allocated into two different groups: a *Biased* group, composed of learners with pre-existing strong attitudes towards the topic (either positive or negative), and a *Neutral* group, with more balanced or undefined attitudes.

Before starting the ISP, participants in the *Biased* group were exposed to content that was intended to support their previous beliefs. In other words, learners who were in favor of the use of AI in education received a video from authorities on the subject supporting this view, while those who were against it also received a video supporting the idea of being against AI in education.

Finally, participants explored the topic freely in an open-ended SAL task, followed by a post-task questionnaire, aligned with the SAL perspective of learning embedded in the search process. All participant interactions, including queries, clicks, dwell times, and session duration, were logged using the application-level framework developed in this research [Machado et al., 2024a].

Figure 4 shows the results comparing the two groups according to each analyzed variable. After statistical analysis, the results revealed that confirmation bias does affect certain aspects of search behavior in SAL. For instance, biased participants tended to complete the task more quickly, spent less time on individual pages, and issued longer queries–although not always in line with initial hypotheses. However, for other variables, such as the number of queries or pages accessed, no statistically significant difference was found between groups. These findings suggest that the dynamics of confirmation bias in SAL are more nuanced than in traditional ad-hoc search tasks, as also noted in comparisons with previous studies in the literature [Azzopardi, 2021].

Importantly, the study demonstrated that the proposed framework effectively supports the end-to-end execution of experiments involving cognitive biases in learning-oriented search. It validated the conceptual model's assumption that learning is influenced not only by user actions but also by interactions with the system interface, backend

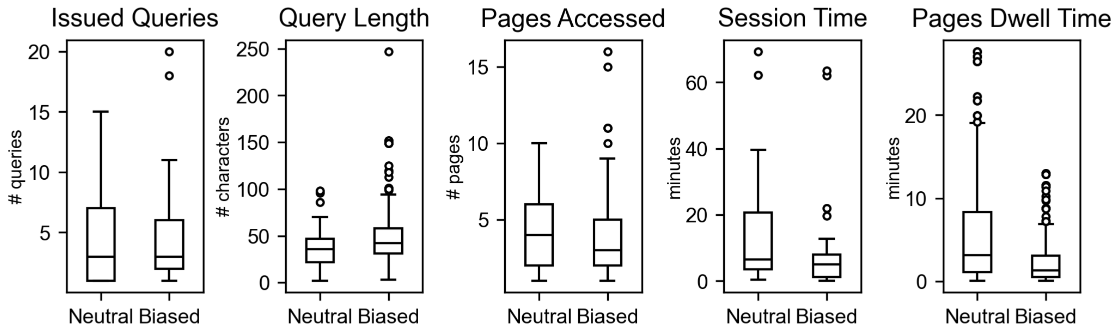

Figure 4. Numerical difference between the two groups considering each of the evaluated metrics.

algorithms, and the broader learner context—including cognitive biases.

Full methodological details, statistical analyses, and discussions are presented in [Machado et al., 2024b]. Here, we emphasize that this experiment contributes both by advancing the methodological tools available for SAL research and by offering new insights into how confirmation bias operates in learning-driven search tasks.

6. Conclusion

This research was motivated by the lack of integration between two important areas: Cognitive Biases in ISP and SAL. While SAL has advanced in understanding how people learn through search, it has largely overlooked how cognitive biases influence this process. Conversely, research on cognitive biases in ISP has predominantly focused on simple, goal-oriented search tasks, disregarding the complex dynamics inherent to learning-oriented searches. This gap has limited the development of both theoretical understanding and practical solutions in the context of learning with search technologies.

To address this gap, our work was guided by two main objectives. The first was to develop a conceptual model that connects cognitive biases with SAL, offering a structured foundation to understand how learner characteristics, cognitive limitations, and search system components interact during learning-oriented search tasks. We approached this objective by analyzing and synthesizing the main models from the SAL literature, such as the works of Hansen and Rieh [2016], Machado et al. [2020], and the Spaceship Model [Von Hoyer et al., 2022], and combining this with insights from the most relevant work on cognitive biases in search, notably Azzopardi [2021]. The resulting model organizes the ecosystem of SAL into two main sides–*user* and *search engine*–while explicitly representing how cognitive biases are part of the learner context, and alongside with system biases can influence the entire ISP and, consequently, the learning process.

The second goal was to create an application-level framework capable of operationalizing the conceptual model into real-world experiments. The framework was designed to support the entire research lifecycle: from learner management and task design to data logging, learning assessment, and analysis. It addresses major challenges in the field, such as fragmentation, lack of standardization, and reproducibility issues. By supporting the import and export of experiments, the framework allows studies to be replicated, compared, and extended, contributing to evolve the research body of the area.

The contributions of this research have relevant implications. The conceptual model serves as a bridge between the fields of cognitive biases in ISP and SAL, providing a common vocabulary and a structured view of how learning, search, and cognitive limitations interact. Built upon recognized models in the SAL literature, it has the potential to attract the attention of researchers in this community, guiding future investigations and supporting the design of bias-aware educational technologies.

The application-level framework plays a crucial role in addressing the fragmentation observed in empirical studies on cognitive biases in search. Its ability to standardize experiments, ensure traceability, and facilitate reproducibility opens new possibilities to build cumulative knowledge in the area. This not only supports more rigorous research, but also fosters collaborative efforts among researchers working on SAL, cognitive psychology, and learning technologies.

To validate both the conceptual and the application-level frameworks, we conducted an empirical study on confirmation bias in SAL, using the topic “The use of AI in education”. This topic was chosen because it allows for the exploration of different perspectives without the extreme polarization found in other domains, making it an ideal context to observe confirmation bias in a learning environment. The choice to study confirmation bias was strategic, as this bias directly affects how learners engage with diverse information, potentially limiting critical thinking (a central concern in education).

The experiment served two purposes: (i) to demonstrate that the framework can effectively instantiate end-to-end experiments aligned with SAL and (ii) to investigate how confirmation bias affects learning-oriented search behavior.

First, the empirical study demonstrated that the framework works effectively in practice. Then, it confirmed that confirmation bias does influence search behaviors in SAL, although with different dynamics compared to traditional ad-hoc searches. This reinforces the need to study cognitive biases specifically within SAL contexts, rather than assuming that findings from simpler tasks are directly transferable. Furthermore, these findings highlight the educational need for bias-aware search practices, aligned with critical media literacy approaches [Freire, 2013, Hobbs, 2010]. Training teachers to recognize how search results reinforce prior beliefs can support reflective classroom strategies and inform public policies on digital literacy and responsible AI use in education.

Looking ahead, this work opens up multiple research avenues. One promising direction is to evolve the conceptual model to account for the growing use of conversational interfaces, such as chat-based search systems, which introduce different interaction dynamics compared to traditional search engines. Another important extension is to incorporate the role of instructors, peers, or communities, especially when considering learning scenarios situated in formal education or collaborative environments. Additionally, future research should explore the compound effects of multiple biases that could interact simultaneously, which reflects real-world cognitive processes more accurately.

Finally, this research has strong social relevance. As search becomes an increasingly central tool for learning in both formal and informal contexts, understanding how cognitive biases shape learning through search is essential. By providing theoretical foundations and practical tools, this work supports the development of search systems and educational interventions that foster more critical, reflective, and equitable learning experiences. In a time when misinformation, polarization, and algorithmic bias are pressing social concerns, advancing research at the intersection of SAL and cognitive biases is not only academically relevant but socially urgent.

Acknowledgments

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