Post-print of a Review on Search-as-Learning Related Research

Authors: Xiaoxuan Song, Liu Chang, Chen Jianlong

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Abstract

[Purpose/Significance] To systematically review relevant research on the topic of "Search as Learning (SAL)" , develop a comprehensive overview, and provide guidance and reference for future investigations in this domain.

[Method/Process] By examining four key issues in SAL research—the relationship between search and learning, factors influencing the search process, assessment of learning, and system optimization—we review existing literature and construct a research framework delineating the relationships among context, user populations, systems, and search-learning within the SAL domain.

[Results/Conclusions] Future research under the SAL topic should focus on four key issues: characterizing learning contexts to design learning-oriented search tasks and evaluate learning outcomes based on task features; exploring the influence of population learning characteristics, such as cognitive and metacognitive features, on behavioral interactions during the search process; understanding search as a learning process and investigating the connections between search behavior and learning behavior; redesigning, configuring, and optimizing current search systems by integrating contextual elements, population elements, and features of search and learning, thereby achieving the integration of search systems and learning systems to effectively support learning.

Full Text

Preamble

A Review of Research from the Perspective of Searching as Learning

Song Xiaoxuan, Liu Chang, Chen Jianlong

Department of Information Management, Peking University, Beijing 100871

Abstract:
[Purpose/Significance] This paper aims to systematically review studies related to the theme of "Searching as Learning (SAL)" to form a comprehensive overview that provides guidance and reference for future exploration of this topic. [Method/Process] We reviewed existing literature from four key issues involved in SAL research: the relationship between searching and learning, factors influencing the search process, evaluation of learning, and system optimization. Based on this review, we constructed a research framework for SAL that examines the relationships among context, users, system, and the search-learning interplay. [Result/Conclusion] Future SAL research should focus on four key issues: characterizing learning contexts to design learning-related search tasks and evaluating learning outcomes according to task characteristics; exploring how individual learning characteristics, such as cognitive and metacognitive features, affect behavioral interactions during the search process; understanding searching as a learning process and investigating the connections between search behaviors and learning behaviors; and integrating contextual factors, user factors, and the characteristics of searching and learning to redesign, configure, and optimize current search systems, achieving integration between search systems and learning systems to effectively support learning.

Keywords: Searching as Learning (SAL); learning-related search; search process; contextual factors; learning outcome; system optimization
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Since its origins, library and information science has been dedicated to helping people store, organize, retrieve, and utilize information to support decision-making and learning [1]. With the rapid development of information technology and network technology, online information has become increasingly abundant, and Internet users have grown accustomed to using web search systems to query and obtain various types of information. For a long time, search systems have been regarded as tools for users to find relevant pages, discover answers, and satisfy their information needs. Current search systems can adequately address fact-finding tasks with relatively clear information needs, but their support for tasks with ambiguous needs and complex processes remains limited [2]. On the other hand, after obtaining information through search engines, people often overestimate their knowledge level, mistakenly believing that knowledge acquired online already exists in their own minds [3]. In reality, people have not truly learned this knowledge; the ease of accessing online information simply creates this illusion. The Dunning-Kruger effect among Internet users has increasingly attracted attention. Therefore, the core value of search engines should not be limited to helping people conveniently access information; they should also develop their value for human learning and thinking.

Information search researchers believe that future search system design and optimization should shift from being answer-centric to learning-centric, creating excellent knowledge contexts for searchers to serve their long-term memory [4]. The concept of "Searching as Learning (SAL)" emerges from this consideration, combining theories from learning sciences to study information searching and focusing on the impact and outcomes of search systems as learning tools rather than mere information retrieval tools [5]. Learning sciences originated in the 1970s, focusing on interdisciplinary research on teaching and learning in formal and informal environments. Drawing knowledge from diverse fields including cognitive science, educational psychology, computer science, information science, and design research, its research emphasis lies in exploring learning environment construction—both human and computer environments—and enhancing student learning outcomes within those environments [6]. In fact, research on the intersection of searching and learning is not new in either library and information science or learning sciences, as earlier studies on information-seeking behavior in learning environments and learning search skills have implicitly discussed connections between searching and learning. SAL research, by exploring patterns of user learning and information behavior, inspires us to reconsider the value of search systems in directly supporting human learning, focusing on their role in learning processes and outcomes, with the goal of optimizing, extending, and reconfiguring search system features and functions to transform from information retrieval tools to learning spaces that serve human learning [7].

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2. Conceptual Connotations of SAL and the Scope of This Review

In SAL research, "searching" and "learning" are two key concepts. Before clarifying their relationship, we must first define the connotation of "learning." For a long time, psychology researchers have explored learning theories, which generally include behaviorist and cognitivist perspectives. Behaviorism describes and understands learning and behavior by analyzing stimulus-response relationships, while cognitivism focuses more on mental processes and the nature of knowledge, including well-known theories such as information processing theory and constructivism. Nevertheless, most psychologists currently support that behaviorism and cognitivism are not mutually exclusive, and understanding human learning from multiple perspectives simultaneously better captures the complex nature of human thinking and learning [8]. In information behavior research, P. Vakkari defines learning as the act of acquiring new knowledge and modifying and consolidating existing knowledge (skills, behaviors, values) through study, practice, teaching, or experience [9]; H. O'Brien explains learning as information acquisition aimed at changing, expanding, or strengthening existing knowledge bases [10]; and J. Gwizdka and X. Chen [11] define learning as changes occurring in human knowledge structures. These definitions all emphasize that learning aims at knowledge change and acknowledge that knowledge is organized, consistent with cognitivism' s main features in learning theory. However, these definitions do not explicitly elaborate on how learning occurs, and different researchers may hold multiple views on the learning process, such as information processing theory or constructivism.

Regarding the relationship between "searching" and "learning," P. Vakkari [9] summarizes SAL research from the perspective of independent and dependent variables in empirical studies into two types: from searching to learning and from learning to searching. "From searching to learning" research examines how search interaction behaviors affect search or learning outcomes, while "from learning to searching" research investigates how learning characteristics—such as students' knowledge levels and task cognitive complexity—affect search interaction behaviors. S. Y. Rieh et al. [2] conceptualize both "from searching to learning" and "from learning to searching" as searching as a learning tool. Additionally, they argue that SAL research should emphasize another concept: searching as a learning process. This concept emphasizes the processual nature of searching, where learners engage in various search activities around learning, such as critically analyzing information, integrating information fragments, and evaluating and using information. This process perspective differs from searching as a learning tool in that it focuses on learning that occurs during the search process, not just search outputs (e.g., search results) and learning outcomes.

Based on the above scholars' discussions, this review will examine existing literature from two aspects according to the relationship between "searching" and "learning" : first, learning as an outcome of searching; second, searching as a learning process. It should be noted that these two relationships are not opposing but complementary. In SAL-related research, learning is the ultimate goal, and the learning process and search process intersect.

To understand the research status of the SAL theme, deepen understanding of the relationship and mechanisms between searching and learning, and reveal current research challenges, we surveyed and analyzed relevant domestic and international literature. For foreign literature, we used keywords "learn," " *search*," "cogniti*," and "knowledge" to conduct topical searches in Elsevier ScienceDirect, Emerald, ProQuest, Springer, Taylor & Francis, Web of Science, Wiley Online Library, and Google Scholar. For Chinese literature, we used keywords "信息搜索" (information search), "信息检索" (information retrieval), "学习" (learning), "认知" (cognition), and "知识" (knowledge) to search CNKI and Wanfang databases. We also conducted backward and forward citation searches from the retrieved results. Since education and psychology have long histories of exploring learning and cognition with vast relevant literature, and to highlight recent developments of SAL in library and information science, we limited retrieval results to the library and information science field, though we may introduce relevant theories from education and psychology when reviewing concepts and issues. Additionally, literature on system algorithms such as machine learning and deep learning is beyond this review' s scope and was excluded. Based on these criteria, we obtained 363 papers as the source literature set for this review.

From the content analysis of selected literature, we found that existing SAL-related explorations mainly revolve around four issues (see Figure 1 [Figure 1: see original paper]): understanding the relationship between searching and learning; exploring how contextual factors (e.g., learning tasks) and individual characteristics (e.g., knowledge level) affect the search process; exploring methods for evaluating learning processes and outcomes in searching; and how to optimize search system functions to support learning. The following sections review existing literature around these four main issues.

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3. The Relationship Between Searching and Learning

3.1 SAL-Related Theories and Models

Early classic theories and models in information retrieval have not been lacking in understanding and characterizing searchers' information needs, search contexts, and search interaction behaviors from cognitive or learning perspectives. In 1980, N. Belkin [12] proposed that information retrieval is driven by users' anomalous states of knowledge (ASK)—users have information needs because they perceive insufficient knowledge in their minds to solve current problems or states. Therefore, users need information retrieval to change their corresponding anomalous states of knowledge. In 1983, B. Dervin [13] understood information needs from a cognitive psychology perspective, proposing sense-making theory, which conceptualizes information seeking as a gap-bridging process. In this process, information seeking emerges when someone cannot understand a situation or context; when they realize a gap exists, they seek information to fill it. Individuals achieve their goals and benefits for information' s intended use by querying and understanding information. Later, M. J. Bates [14] proposed the berry-picking model in 1989, emphasizing that information searching is an evolutionary process where searchers' information needs change through a series of search interactions. Each interaction between searchers and information objects deepens their understanding of the search topic, providing new ideas and directions for searching. Although Bates did not explicitly state that this evolutionary process is a learning process, the new understanding of search topics and adjustments to search ideas and directions inherently possess learning characteristics.

Researchers have also proposed models describing the information search process in academic search contexts, among which the most influential is C. C. Kuhlthau' s [15] Information Search Process (ISP) model. This model focuses on changes in affective, cognitive, and behavioral dimensions across six stages: initiation, selection, exploration, formulation, collection, and presentation. In subsequent studies, P. Vakkari refined the ISP model' s six stages into three problem stages: pre-focus, formulation, and post-focus, analyzing differences in interaction features such as information types [16], search strategies [17], and relevance judgments [18] across these stages when students searched for master' s thesis topics.

From the perspective of search interaction activities, G. Marchionini [19] argued that the search process consists of multiple search activities that can be broadly categorized into three sets: lookup, learn, and investigate. Based on this, he proposed exploratory search, which emphasizes learning and investigation activities. Exploratory search highlights that searchers may undergo various search activities related to knowledge acquisition, understanding, interpretation, comparison, integration, and analysis during the search process, rather than obtaining answers directly from search systems. Although this theory focuses on search results—viewing learning and investigation outcomes as criteria for search success—it does not emphasize how specific learning activities evolve during the search process. Nevertheless, it made important contributions to infusing learning thinking into the information search process. K. Järvelin et al. [20] proposed a Task-Based Information Interaction (TBII) model that considers both behavioral and cognitive processes in learning contexts, dividing learners' information interaction activities into five stages: task planning, searching for information items, selecting information items, working with information items, and synthesizing and reporting. Each interaction stage involves different types of behavioral and cognitive activities and requires different evaluation criteria for assessing activity outcomes. Compared with focusing only on final task outcomes, the TBII model provides limited refinement of the search and learning processes but has not fully revealed the conceptual connotation of "searching as learning"—that the search process and learning process coexist and intersect in given time and space.

SAL researchers focus on users'knowledge changes during searching and learning processes. In education and psychology, the most influential theory regarding knowledge change is J. Piaget' s [21] learning construction theory, which views learning as an active construction process based on existing knowledge and experience, comprising assimilation and accommodation. Assimilation refers to adding new information to existing knowledge structures when it is consistent with them, while accommodation refers to adjusting existing knowledge structures when new information conflicts with them. Later, D. Rumelhart and D. Norman [22] further refined accommodation into tuning and restructuring. Tuning involves organizing, interpreting, or slightly modifying information, causing minor changes to existing knowledge structures, while restructuring completely changes existing structures or creates new ones [23]. Based on this three-category framework of knowledge change, P. Vakkari [24] considered the completion process of complex search tasks as a gradual stabilization of searchers'knowledge structures. Specifically, in early search stages of exploration and formulation, searchers' knowledge changes more likely exhibit restructuring characteristics; in the middle information collection stage, the general knowledge framework has been built, and knowledge changes may mainly involve tuning to collect more information and expand knowledge scope; in the final reporting and presentation stage, knowledge changes manifest more as assimilation, such as instantiating existing knowledge structures. This theoretical hypothesis provides an important entry point for exploring relationships between learning processes and search behavior processes, awaiting further refinement and verification in future research.

3.2 Learning as an Outcome of Searching

From an outcome perspective, SAL research views learning as an output of searching, emphasizing final learning achievements, outputs, performance, or knowledge acquisition, and explores relationships between interaction behaviors during searching and learning outputs. In information retrieval, search performance evaluation can be broadly divided into output evaluation and outcome evaluation. Output evaluation assesses system-delivered products, such as recall and precision rates of information items, while outcome evaluation focuses on benefits the system brings to users, such as helping users better achieve search goals or gain certain abilities during task completion [20]. SAL focuses on search systems' support for learning, so its performance evaluation should not remain at traditional search output levels but should focus more on improvements in searchers' learning abilities.

Existing studies have found that search activities have significant positive effects on learners' learning outcomes or knowledge level improvements. J. Gwizdka' s team borrowed the cognitive, skill-based, and affective theory of learning outcomes (CSALO) model from psychology [25] to evaluate learning outcomes in information searching from three aspects: verbal knowledge, knowledge organization, and cognitive strategies. In preliminary research [11], they invited participants to list words related to search task topics before and after searching, using the quantity and professionalism of listed words to represent learning outcomes. At this stage, they found that if participants entered more queries during searching, they could list more relevant words after searching. Later [26], they used eye-tracking methods and found that users with lower learning outcomes expended more effort during reading, showing more frequent reverse eye movements and longer movement distances compared to high-learning-outcome users. K. Collins-Thompson et al. [27] found that users who spent more time reading documents produced higher-quality post-search task essays. Tan Jinbo [28] found in analyzing behavioral strategies affecting students' web-based learning performance that the longer students browsed search result pages and the shorter their careful reading time, the lower their learning performance. U. Gadiraju and R. Yu' s team had participants complete a series of true/false questions related to tasks before and after searching to test knowledge gains, also finding that users' content page dwell time and query formulation complexity were significantly positively correlated with knowledge growth [29]. They then conducted a larger-scale study [30] with 468 participants, capturing approximately 70 interaction variables (including session, query, search results page, browsing, and mouse-related variables) to predict users' post-search knowledge growth. However, results showed almost all variables had only weak correlations with knowledge growth, possibly due to low task complexity and short search sessions preventing many variables from demonstrating their contribution. Nevertheless, the study emphasized that content page dwell time significantly contributed to knowledge growth. C. Liu and X. Song extracted seven indicators from post-search task essays: number of knowledge points, number of knowledge facets, knowledge facet breadth, knowledge facet depth, knowledge relevance, analysis level, and user viewpoints to comprehensively evaluate learning outcomes, and explored how information selection behaviors affected learning outcomes. Results showed users' information source preferences significantly affected post-search knowledge facet breadth, depth, and relevance [31]. Information recording also significantly affected learning outcomes, with earlier recording during searching leading to better learning results [32].

Based on existing research, an important prerequisite for exploring the relationship between searching and learning from an outcome perspective is defining and evaluating learning effects or outcomes. Different research contexts have different understandings and descriptions of learning outcomes, naturally requiring different evaluation methods—this represents a key challenge for outcome perspective research, which we will review in detail later. Additionally, exploring connections between search interaction behaviors and learning outcomes helps identify potential behavioral indicators for predicting learning effects. Current research focuses more on how query formulation and reading-related behaviors (e.g., dwell time on content pages, frequency, reading strategies) contribute to learning outcomes, as reading is the direct channel for learners to receive information. However, search processes for learning purposes can be complex, and future research should also address how users process and use information beyond searching and reading activities.

3.3 Searching as a Learning Process

The process perspective of SAL emphasizes studying searching as a learning process. Compared with the outcome perspective' s focus on learning outputs, the process perspective emphasizes characterizing the interaction between search and learning processes, exploring when and how learning occurs during searching, and whether behavioral indicators can imply learning occurrence. In process perspective research, learning remains the ultimate goal, but researchers hope to understand learning' s mechanisms across different activities or stages through detailed monitoring and analysis of various search process activities to achieve overall optimization through local improvements.

Since characterizing and describing learning processes is complex, most researchers tend to implicitly represent learning processes through behavioral activity processes, provided they can demonstrate associations between studied behavioral indicators and learning concepts. For example, Y. Chi et al. [33] treated click complexity and query complexity as implicit representations of users' knowledge levels during searching, finding that both increased as searching progressed. Particularly, query complexity in the first 1/6 of search sessions was significantly lower than in later periods. N. Roy et al. [34] found that users' average dwell time on content pages gradually decreased as searching progressed. Users with higher pre-search knowledge levels entered more queries in early stages and spent more time reading content documents, while users with lower knowledge levels spent more time on search results pages.

Besides search behaviors, users' writing or recording behaviors are also considered another manifestation of learning occurrence. M. Potthast and M. Hagen et al. [35-36] explored how article writers used ClueWeb09 search to complete article writing, identifying two text recording strategies based on completed text length after each editing session: buildup and boil-down. Writers using buildup strategies continuously increased article length throughout the writing process, while those using boil-down strategies first accumulated substantial materials (showing rapid text length growth) before reorganizing and shortening the article. They also compared differences in search behaviors across writing process stages, finding users formulated more queries and had more click activities in early stages, while recording activities concentrated in later stages. Liu Chang et al. [37] treated information recording behaviors in notepads during searching as learning behaviors, identifying three recording strategies based on recording completion progress across stages: early-recording, average-recording, and late-recording types, finding that average-recording strategy—as a general pattern where recording behaviors gradually advance with searching—produced relatively better learning outcome quality.

Some studies directly describe and characterize searchers' learning processes from knowledge structure perspectives. P. Zhang and D. Soergel [38] analyzed information seeking and sense-making processes, making users' knowledge change processes explicit through think-aloud methods and summarizing nine query-sense-making iteration patterns: task analysis or missing knowledge identification-search-knowledge structure construction-example supplementation; search-knowledge structure construction; search-example supplementation; search-knowledge construction-example supplementation; search-example-knowledge structure construction; simultaneous knowledge structure construction and example supplementation; single search; knowledge structure construction-example supplementation; and sense-making while writing task outcomes. In C. Liu et al.' s series of studies, participants' knowledge change processes were externalized relatively completely through mind-mapping methods during searching. In exploring searchers' knowledge change styles [39], they encoded each mind map modification during searching, coding knowledge change types (addition or optimization) and knowledge structure changes (facet-level or point-level changes), and summarized four knowledge change styles in learning contexts based on when changes occurred: early-change style, mid-change style, late-change style, and average-change style. This study provides preliminary exploration of when learning occurs during searching. In modeling searchers' knowledge change processes and strategies [40], they more finely encoded from the perspective of knowledge points and inter-point relationships, identifying 25 types of knowledge change behaviors based on knowledge structure change characteristics and locations. Using sliding time window clustering from a whole-process perspective, they further revealed users' knowledge change strategies. Additionally, in another study on knowledge utilization features, they found through vocabulary analysis that searchers rarely completely overturned mind map knowledge structures, more frequently adding detailed information to existing structures, with over one-third of added vocabulary directly copied from content pages they read [41]. These studies all reveal to some extent the important question of how learning occurs during searching.

In summary, current SAL process perspective research focuses on various activities during searching, such as information searching (e.g., query complexity), information selection (e.g., dwell time on content pages), information use (e.g., recording behaviors), and gradually begins to focus on knowledge change characteristics during learning processes. Future research needs to strengthen the coexistence of search and learning processes in SAL studies, further exploring associations between various search behaviors and knowledge change characteristics—for example, which behavioral features during searching can serve as implicit or explicit indicators of users' knowledge structure changes—thereby providing references for systems to support user learning through behavioral monitoring.

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4. Factors Influencing the Search-Learning Process

In information behavior research, context is a factor influencing human behavior, broadly including time, space, tasks, natural and social environments, and individual characteristics [42]. Time context refers to information behaviors occurring at different times; space context refers to behaviors occurring at different locations; task context mainly refers to information seeking and use behaviors performed to accomplish certain goals or tasks; natural and social environments refer to other external factors that may affect information behavior, such as whether the environment involves independent searching in quiet spaces or collaborative searching in multi-person settings; individual characteristic factors relate to user characteristics. This section reviews influencing factors in two subsections: individual characteristics and other contextual factors.

4.1 Influence of Individual Characteristics

Many SAL-related studies explore users' individual learning characteristics—such as knowledge level, search ability, and cognitive style—and their effects on search behaviors, strategies, and learning outcomes. T. Willoughby et al. [43] studied how domain knowledge level and using the web as an information source affected performance in essay writing activities. They found that the web-using group performed better than the non-web group, but this difference was only significant among users with high domain knowledge; for users with relatively low domain knowledge, web use showed no significant difference in final essay performance. M. J. Wilson and M. L. Wilson [44] found that users with higher domain knowledge covered more knowledge topics in post-search task summaries. U. Gadiraju et al. [29] found that users with lower pre-search topic familiarity tended to expend more search effort and achieved higher knowledge increments after searching. Yuan Hong and Li Qiu [45] found that stronger search ability led to deeper and more efficient exploratory search processes, manifested in richer, deeper, and more accurate query formulation, stronger inter-query relevance, more frequent search actions, more content page clicks, frequent tab switching, and longer average page dwell time.

Regarding cognitive style, K. Kinley and D. Tjondronegoro [46] found that holistic cognitive style users tended to adopt top-down search strategies during searching, first conducting broad searches around topics to understand general situations before gradually shifting to specific information; analytic cognitive style users preferred bottom-up strategies, continuously accumulating specific information before final integration. Liu Hanrui and Liu Chang [47] found that cognitive style mainly affected search behaviors under learning-related search tasks, while topic familiarity mainly affected reading and recording behaviors. Zhang Lulu and Huang Kun [48], based on field-independent and field-dependent cognitive style types proposed by G. W. Allport et al. [49], explored their impact on digital library users' information retrieval behaviors, finding significant differences between the two cognitive style types in basic retrieval features (selection of search points and functions) and single-session features (search duration, number of queries, and query reformulation patterns).

The above studies explore search interaction processes from perspectives such as searchers' knowledge levels and cognitive styles, which have matured in SAL-related research. The ultimate expectation of SAL research is to optimize current search systems into learning spaces that support human long-term learning. Recently, researchers have begun focusing on learners' metacognitive characteristics to understand self-regulated learning processes from planning to monitoring to evaluation, revealing mechanisms of learning, critical thinking, and creation during these processes to provide effective basis for optimizing learning support systems. The concept of metacognition was proposed by developmental psychologist J. H. Flavell in 1976, defined as "knowledge or cognitive activities that reflect or regulate any aspect of cognitive activity" [50]. In psychology and education, many achievements have been made regarding how metacognitive activities promote learners' learning ability improvement. In information retrieval, limited current research finds that searchers' metacognitive characteristics directly affect their search process behaviors and strategies. For example, G. Z. Liu and S. S. Chong [51] used case studies to analyze five participants' metacognition and conceptual drifting characteristics during final assignment completion, finding that to prevent conceptual drift in search topics, users might adopt two different metacognitive strategies: continuously reminding themselves of the original search topic internally, or maintaining repetitive searches. L. Bowler [52] used long-term observation to study college students' metacognitive knowledge during term paper writing tasks, identifying 13 types of metacognitive knowledge that learners need to mobilize during learning-related searching: balancing, foundation building, changing course, communicating, connecting, knowing what one doesn' t know, knowing one' s strengths and weaknesses, parallel thinking, reflecting, scaffolding, understanding curiosity, understanding memory, and understanding time and effort. It is foreseeable that deeply analyzing the nature of learning and monitoring its dynamic process, rather than limiting judgments to coarse-grained learning ability levels, will become mainstream in future SAL research.

4.2 Influence of Other Contextual Factors

Beyond individual characteristics, SAL research has most intensively focused on search task context-related factors to define and classify different learning goals in learning-oriented searches and how these goals affect search-learning processes. In information search research, search tasks refer to task descriptions and series of actions performed during task completion [53-54], with search process and behavior observation typically conducted through analyzing ongoing search tasks. Liu Chang et al. proposed the concept of "learning-related search" [37,55-56], integrating both outcome and process perspectives into learning search contexts. Learning-related search is a search context that emphasizes learning, constructed by designing learning-related search tasks. These tasks involve users collecting, analyzing, evaluating, and using information through search systems to complete learning tasks. For learning-related search task design and interaction activity analysis under such contexts, relatively implicit learning processes are maximally externalized, helping to deeply understand search processes, learning processes, and their interactions.

Empirical SAL search tasks in existing research mainly include two types: first, adding search tasks to real learning tasks, such as having school students search while completing assignments or searching to acquire certain skills. Examples include C. C. Kuhlthau' s [15] ISP model and P. Vakkari' s three problem stages [16-18], which all stage information behavior characteristics when students complete learning tasks over time. In real learning tasks, time context' s role in information seeking and searching should be considered, though such research remains insufficient and should be conducted considering authentic learning and time contexts in future studies.

The second type designs search tasks based on different learning dimension characteristics. Among the most influential theoretical bases is the cognitive learning taxonomy proposed by L. W. Anderson and D. R. Krathwohl [57] based on B. Bloom's taxonomy of educational objectives, which divides cognitive complexity from low to high into six levels: remember, understand, apply, analyze, evaluate, and create. Studies by B. J. Jansen et al. [58], W. C. Wu et al. [59], D. Kelly et al. [60], S. Ghosh et al. [61], and Han Zhengbiao et al. [62] all designed SAL search tasks based on this taxonomy. These studies found that task cognitive complexity affects users' information search behaviors and post-search learning outcomes. As cognitive complexity increases, users spend more time searching, formulate more queries with longer lengths, click more search results pages, and visit more URLs, but learning outcome effects become worse and users' self-assessment confidence in their knowledge level becomes lower.

S. Y. Rieh et al. [2], from the perspective of searching as a learning process and drawing on the cognitive learning model from education, divided learning processes into three types: receptive learning, critical learning, and creative learning. Receptive learning refers to students' memory, understanding, and expression of learned knowledge, corresponding to Bloom' s remember and understand levels—relatively shallow learning. Critical learning refers to forming students' own thinking through reflecting on, critiquing, and evaluating knowledge from different sources, corresponding to Bloom' s apply, analyze, and evaluate levels—deeper than receptive learning. Creative learning corresponds to Bloom' s create level—the most demanding learning mode requiring students to generate new ideas or construct new structures. The difference is that Anderson and Krathwohl' s taxonomy focuses on learning objectives and outcomes assessment, while the cognitive learning model better suits exploring cognitive processes and learning strategies. Based on the cognitive learning model classification, S. Y. Rieh et al. [2] proposed the new concept of comprehensive search, emphasizing users' iterative, reflective, and integrative information processes during searching, focusing on critical and creative learning levels. This comprehensive search concept shares similarities with G. Marchionini' s [19] 2006 exploratory search, but exploratory search focuses on search results (reflecting "learning as search outcome"), while comprehensive search emphasizes understanding searching as a learning process. Additionally, S. Y. Rieh et al. [2] noted that exploratory search mainly addresses receptive and critical learning levels, rarely involving creative learning.

Besides search or learning task types, some scholars classify needed information or knowledge types during searching, such as K. Urgo et al. [63], who recently refined the framework for designing search tasks based on cognitive learning taxonomy. Beyond the cognitive complexity dimension, this taxonomy involves a knowledge dimension including factual, conceptual, procedural, and metacognitive knowledge. They advocate combining cognitive complexity and knowledge dimensions to design search tasks.

Beyond search tasks, collaborative search processes, device types used (e.g., desktops, laptops, tablets, smartphones), and search system functions and information presentation methods all affect search-learning processes. However, current research on these contextual variables is limited and requires further verification in future studies.

5. Assessing Learning in Search

5.1 Measuring Learning Outcomes

As described in Section 3.2, SAL learning evaluation focuses not on search output but on post-search learning outcomes, analyzing changes in users' knowledge features and whether these changes help complete learning-related search tasks.

Existing research has explored various methods for evaluating learning outcomes, which can be roughly categorized as follows:

(1) **Scales or questionnaires** for self-assessment after searching [61,64]. For example, Yuan Hong and Shi Xiaoling [65] designed a scale from five dimensions: effective learning time, knowledge acquisition, analysis/synthesis, knowledge innovation, and increased search ability, allowing users to self-evaluate learning effects after searching. This evaluation method is relatively subjective, relying heavily on scale validity and self-assessment accuracy. Research finds that users' self-assessments of knowledge level may be inaccurate, with overestimation or underestimation occurring [66], which relates to whether users possess good metacognitive knowledge for self-awareness and judgment [28].

(2) **Testing methods** where users answer search task-related questions with clear, unique answers, with test scores representing current knowledge levels. For example, W. R. Hersh et al. [67] had medical students answer medical-related questions with clear answers before and after searching, scoring correctness to demonstrate searching' s role in knowledge improvement. L. Nelson et al. [68] and U. Gadiraju et al. [29] also used pre- and post-search true/false questions to measure learning outcomes.

(3) **Task essays or reports** quality assessment. For example, Y. Kammerer et al. [69] evaluated learning outcomes based on argument quantity, organizations/individuals listed, and valuable keywords in user-written essays. T. Willoughby et al. [43] scored student essays by counting acceptable and correct statements/phrases. M. J. Wilson and M. L. Wilson [44] proposed a depth-of-learning evaluation method, manually judging usefulness, analyticity, and evaluative quality of pre- and post-search essays to analyze knowledge growth. Song Xiaoxuan and Liu Chang [56] argued that essay evaluation should not be limited to counting facts or statements but should be comprehensive, proposing a method covering seven aspects: knowledge point count, knowledge facet count, facet breadth, facet depth, knowledge relevance, analysis level, and user viewpoints.

Recently, researchers have increasingly focused on relationships between searching and user knowledge structures. Xia Lixin et al. [70] and Zhang Yunqiu et al. [71] collected participants' pre- and post-search concept maps through visualized knowledge structures, assessing learning outcomes by comparing knowledge structure differences. Liu Ping et al. [72] quantitatively evaluated concept nodes (richness, professionalism, effectiveness) and concept relationships (connectivity, hierarchy, exploratory nature) in post-search concept maps from three linguistic semiotic levels: syntax, semantics, and pragmatics, validating the quantitative system with expert ratings.

D. A. Kolb, an experiential learning expert, summarized four learning situation types: affective, perceptual, symbolic, and behavioral complexes, noting that learning outcome assessment should vary by context [73]. For example, in perceptual learning, learners are required to view problems from different angles and ways, emphasizing how and the process of completion, not just results. Such learning outcomes have no fixed standard answers, making testing-based assessment inappropriate. However, in symbolic complex contexts, learning success is judged by correct or optimal solutions, expert opinions, or strictly accepted standards within the field. Therefore, effective learning outcome assessment methods must first consider learning context and search tasks to ensure alignment between learning objectives and assessment.

5.2 Process-Based Implicit Measurement of Learning

From a process perspective, researchers aim to explore when and how learning occurs during searching and which activities or patterns can implicitly indicate or monitor learning occurrence. Mining implicit learning indicators during searching helps search systems understand and monitor learners' processes from behavioral features to provide timely, effective support.

Existing research has found that interaction variables such as query formulation/reformulation patterns, query length, term diversity, number of documents read/saved/downloaded, and time spent evaluating documents can serve as implicit indicators of learning occurrence during searching due to their associations with learning and cognitive feature development [33,74-75]. For example, Y. Chi et al. [33] found that click complexity and query complexity increased during searching, suggesting knowledge growth. They also found query complexity in the first 1/6 of search sessions was significantly lower than later periods, possibly indicating learning likely occurred after this initial period. Yuan Hong and Shi Xiaoling [65] divided total search time into thirds, naming them basic knowledge learning, thematic deep learning, and interest-based specialized learning. They found that in basic knowledge learning, users tended to repeatedly visit webpages; during deep learning, they browsed pages longer and clicked deeper links; in specialized learning, they examined search results pages more carefully. However, this stage division of learning processes requires more rigorous validation to support these behavioral indicators as representatives of learning occurrence or stage transitions.

In predictive studies, R. W. White et al. [76] found that query features (length, vocabulary coverage), session features (number of content pages browsed, number of queries, search time, page revisits), and source selection (content page types, URL features) could effectively predict users' current knowledge levels. X. Zhang et al. [77] found that number of saved documents, average query length, and average position of read documents on results pages best predicted domain knowledge. P. Vakkari [9] viewed learning as knowledge structure change. He subdivided search processes into stages by subtask, including search formulation, information source selection, and information source use, theoretically proposing implicit behavioral indicator features revealing knowledge structure restructuring in each stage, as shown in Table 1 . This research establishes connections between search process and learning process features, helping inspire future research to monitor and evaluate learning activities from behavioral perspectives.

Table 1. Implicit Indicators of Learning (Knowledge Structure Restructuring) Occurring in Each Search Stage

Search Stage	Implicit Indicators of Learning (Knowledge Structure Restructuring)
Search Formulation	Increased and more specific search terms; reduced time spent in search formulation stage; increased associated search terms; reduced query reformulation; reduced strategy adjustment; increased synonyms
Information Source Selection	Increased clarity of relevance criteria (ability to distinguish relevant sources); reduced number of documents viewed on results pages; reduced total information sources selected; decreased proportion of possibly relevant sources, increased overall relevance scores; decreased proportion of background/theoretical information; increased proportion of concrete/factual information; inverted U-shaped proportion of procedural information
Information Source Use	Increased proportion of used sources; increased number and specificity of concepts and relationships in knowledge structure; decreased proportion of background/theoretical information; increased proportion of concrete/factual information; inverted U-shaped proportion of procedural information

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6. Optimizing Search-Learning Systems

Traditional search systems are designed and refined as tools that retrieve relevant information to satisfy specific information needs. Under the SAL research theme, researchers aim to rethink, model, and design current interactive search systems. In the future, these systems will not be pure search systems but learning systems that support learners' information searching, browsing, understanding, analysis, and creation [78].

Current research on search system design and optimization still mainly focuses on supporting information acquisition (e.g., query formulation) and information selection (e.g., SERP ranking, result visualization). Support for learning aspects

–such as information quality assessment, comparison, analysis, synthesis, and creation–requires further consideration. A. Meyer et al. [78] proposed a vision for a creative virtual academic space called the third space, defined as the intersection between school learning and students' existing knowledge and cognitive styles–a dynamic learning space. It is foreseeable that future search system optimization goals will be to become the core of this third space. Therefore, system design and optimization should incorporate information literacy, cognitive characteristics, and theories and patterns from real educational contexts.

Researchers have begun trying to provide support at the interface level for information searching, presentation, and other aspects to help searchers complete learning-related tasks. For example, C. P. Teixeira et al. [79] proposed a "learner-friendly" search results page (SERP) ranking criterion that presents results in the order of conceptual content, procedural content, deepened content, and related content, based on relevance. Starting with conceptual content ensures learners don' t access overly complex content when initially interacting with information sources, allowing preliminary understanding of basic concepts and relationships; procedural content (e.g., guidelines, step-by-step materials) about how to apply concepts helps learners understand concept-application relationships; deepened content refers to specific information obtained from search content that helps refine query formulation; finally, related content provides information relevant to the current search topic. G. Fulantelli et al. [80] developed a search tool called SaR-Web (Search as Research-Web) to support users' scientific research search processes. SaR-Web integrates search results from different cultural backgrounds, languages, and search engines, visually presenting these diverse sources to support learners' comparison and analysis of search results. H. C. Huurdeman et al. [81] designed two three-stage search tasks based on Vakkari' s three problem stages (pre-focus, formulation, post-focus) to study search UI feature utility across stages. They found that information features (e.g., search results) played important roles in all three stages, while input features (e.g., search boxes) and control features (e.g., category filters, tag clouds, query suggestions) declined in usefulness after the pre-focus stage, being replaced by personalized features (e.g., recent searches, saved results). This differs slightly from X. Niu and D. Kelly' s [82] earlier findings that users preferred self-formulated queries in early and middle stages, using query suggestions more in later sessions. This discrepancy likely relates to users' search expertise and task characteristics. H. C. Huurdeman [83] further proposed a "stage-aware" search UI framework for supporting complex tasks, dividing system support into low, medium, and high levels. Low-level support focuses on supporting users' moves during searching, providing input and control functions like query suggestions, categorization/filtering, result ranking, and tag clouds; high-level support focuses on supporting users' strategies, providing personalized functions like result saving, annotation, search history, and expansion tools; medium-level support provides information functions like search results, thumbnails, and visualizations.

C. L. Smith and S. Y. Rieh [4] advocated creating a knowledge context in search systems to support learners' long-term memory, creativity development, and critical thinking during learning. Knowledge context is defined as various types of meta-information accessible and usable by searchers on search results pages, including bibliographic context (e.g., author, publisher, time) and inferential context (e.g., citation counts, similar documents, authors' other works).

Beyond system design and optimization in learning contexts, some researchers focus on systems serving specific populations. K. Collins-Thompson et al. [84] argued that current search systems don' t consider document reading difficulty and users' reading ability when providing results, which disadvantages populations with lower reading ability, such as children, in achieving learning goals. I. M. Azpiazu et al. [85] addressed literacy and reading comprehension issues in 5-15-year-old children, developing a child-oriented online search tool called YouUnderstood.Me (YUM). YUM identifies children' s search intentions from their queries, provides relevant query suggestions, infers children' s reading levels through explicit relevance feedback, and filters information by document readability to enhance children' s search experience and promote learning. M. L. Wilson et al. [86], using domain novices searching for technical problems (e.g., programming code issues) as examples, proposed optimizing Google search engine from three angles to support searchers' technical learning: supporting detailed explanations, supporting multi-turn dialogue, and supporting further understanding of professional terms and definitions. Detailed explanations refer to providing additional functions or guidance to help searchers refine and formalize search context descriptions; multi-turn dialogue helps searchers continuously clarify search content and goals; and further understanding of professional terms and definitions helps searchers ask professional questions and analyze search results.

Conclusion and Future Directions

The core issue of the SAL theme is how to make information better serve human lifelong learning and development in today' s knowledge-intensive era. Therefore, information search systems should not stop at being tools for information acquisition but should prioritize learning support, reconfiguring and optimizing current search systems into learning systems that conform to learning and information behavior patterns and support knowledge discovery, critical thinking, and knowledge creation. By reviewing SAL-related literature around four main issues in current research, this paper reveals:

(1) **Understanding the relationship between searching and learning.** Existing research can be divided into outcome and process perspectives. The outcome perspective views learning as search output; the process perspective studies searching as a learning process. These perspectives are complementary rather than opposing, together completely revealing relationships and effects between search and learning processes. Current

literature has richly explored how interaction behaviors affect post-search learning outcomes, but research on searching as a learning process remains limited. The relationship between search behavior pattern evolution and learners' knowledge structure changes requires finer-grained investigation.

(2) **Exploring how contextual and individual factors affect searching.** Existing research has found that task characteristics significantly affect search interactions. This review examined exploratory and comprehensive search task design rationales, features, and connections. Considering learning activities' implicit and complex nature, researchers proposed the learning-related search concept, integrating search and learning process features within learning contexts. Future research needs to further understand and refine learning context features and explore how learning-related search tasks affect search and learning processes. Regarding individual characteristics, much research has explored how searchers' knowledge levels, cognitive styles, and search skills affect search interactions. The SAL theme hopes to more deeply understand learners' learning processes, such as information analysis, comparison, synthesis, and creation, which require further consideration. A. Meyer et al. [78] proposed a vision for a creative virtual academic space—the third space—as the intersection between school learning and students' existing knowledge and cognitive styles. Future search system optimization should aim to become the core of this third space, with design and optimization incorporating learners' information literacy, cognitive characteristics, and theories from real educational contexts.

(3) **Exploring learning process and outcome assessment methods.** Existing research has attempted to assess search learning outcomes through questionnaires, tests, task essays, concept maps, and other methods from qualitative and quantitative perspectives. However, these methods' applicability and scientificity lack validation. Learning outcome assessment design should analyze current learning task contexts and objectives to develop context-matched assessment criteria. Therefore, how to characterize learning-related search task contexts and design assessment criteria consistent with contextual features is an important future SAL research question. Besides learning outcome assessment, limited research has explored implicit behavioral indicators of learning during searching. Mining behavioral change features helps search systems monitor users' search processes in real time to understand current learning states and provide corresponding support. Future research should focus more on relationships between interaction behaviors and learning during searching, evaluating learning occurrence and evolution from interaction behavior perspectives.

(4) **Optimizing search system functions to support learning.** Existing research has attempted many interface-level optimizations to support information acquisition and selection. Future search systems are expected

to support all learning process stages, requiring functional support for information understanding/analysis, comparison/synthesis, and creation beyond acquisition and selection. Additionally, system optimization should incorporate various contextual and population characteristics, such as perceiving learners' current knowledge or metacognitive levels through behavioral feedback to provide precise learning support.

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Author Contributions:
Song Xiaoxuan: collected and analyzed data, drafted the manuscript;
Liu Chang: proposed research ideas, participated in data analysis, revised the manuscript;
Chen Jianlong: refined research ideas, revised the manuscript.

Song Xiaoxuan Liu Chang Chen Jianlong
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Department of Information Management, Peking University, Beijing 100871