The Impact of Prior Knowledge Differences on Collaborative Information Search and Learning Outcomes (Postprint)

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Abstract

[Purpose/Significance] This study investigates the differences among groups with varying prior knowledge disparity levels in search interaction behaviors, collaborative experiences, and learning outcomes, aiming to enrich the understanding of collaborative information search behavior and provide recommendations for collaborative search learning in real-world contexts.

[Method/Process] The research adopts a user experiment methodology, designing comprehension-based and evaluation-based search tasks. Interaction behaviors are recorded through screen capture, collaborative experience data is collected via questionnaires, and mind maps document knowledge states and changes before and after collaborative search. Data analysis employs methods such as ANOVA and Kruskal-Wallis tests.

[Results/Conclusion] The findings indicate that: regarding search interaction behaviors, groups containing members with higher prior knowledge levels use more search queries than homogeneous low-level groups; concerning collaborative search experience, groups with similar prior knowledge levels evaluate their task completion more highly; in terms of knowledge state changes, homogeneous low-level groups show significantly greater growth in knowledge breadth than the other two groups, yet post-search differences in quality among groups are minimal. Finally, this study offers recommendations for improving search systems to enhance users' collaborative search experience and learning outcomes.

Full Text

The Effect of Prior Knowledge Differences on Collaborative Information Search and Learning Outcomes

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Abstract:
[**Purpose/Significance**] This study explores differences in search interaction behaviors, collaborative experiences, and learning outcomes among groups with varying levels of prior knowledge differences, aiming to enrich understanding of collaborative information search behavior and provide recommendations for collaborative search learning in real-world contexts.
[**Method/Process**] A user experiment was conducted with two types of search tasks (comprehension and evaluation). Interaction behaviors were recorded through screen capture, collaborative experience data was collected via questionnaires, and knowledge states before and after collaborative search were documented using mind maps. Data analysis employed ANOVA and Kruskal-Wallis tests.
[**Results/Conclusions**] The study found that: (1) In terms of search interaction behaviors, groups containing members with higher prior knowledge used more search queries than homogeneous low-level groups; (2) In collaborative search experience, groups with similar prior knowledge levels rated their task completion higher; (3) In knowledge state changes, homogeneous low-level groups showed significantly greater growth in knowledge breadth than other groups, but differences in quality among groups were minimal after searching. Finally, the study proposes improvements for search systems to enhance collaborative search experience and learning outcomes.

Keywords: collaborative information search; knowledge state change; learning-related search
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1 Introduction

With the development of information technology, web search has become an important means for people to obtain information in both learning and daily life. Search systems have facilitated the overlap between searching and learning, bringing these two activities increasingly closer together [1]. Consequently, how to help people learn better through search has become a significant issue, making "search as learning" a sustained research hotspot. Some scholars view search as a tool for learning, while others consider it a learning process [2]. Under the "search as learning" umbrella, research has found that learning activities conducted online can better stimulate students' enthusiasm for learning, and has explored elements such as search systems and contexts involved in the learning process [3-4]. Among various contextual variables, collaborative search scenarios have received growing attention [5]. Collaborative search refers specifically to situations where multiple people share an information need and work together to satisfy it [6]. In daily learning contexts, short-term collaborative tasks are common among university students, such as group presentations on a particular topic or selecting topics for final group projects. These tasks require collaborative search to collect relevant information and learning through discussion and reflection. Group composition is often random, with varying degrees of prior knowledge differences among members, which may lead to differences in collaboration processes and outcomes. Current research on collaborative search behavior often focuses on analyzing collaboration patterns and communication content [7], emotions expressed during collaborative search [8], and collaborative search experiences [9], but rarely explores specific factors affecting collaborative information search learning outcomes, particularly the impact of prior knowledge differences among group members before searching on collaborative search effectiveness and learning outcomes. Therefore, this study aims to investigate the differences in interaction behaviors, collaborative experiences, and learning outcomes among different groups formed based on prior knowledge level differences in short-term learning-related search tasks, thereby enriching research on collaborative search behavior.

2 Literature Review

This research involves three relevant literature streams: learning-related search, collaborative information search, and knowledge state change.

Learning-related search is a type of search task that focuses on "search as learning," referring to search activities where users collect, analyze, evaluate, and use information through search systems to complete learning tasks [2]. Related research primarily focuses on learning behavior characteristics, process features, and influencing factors in learning-related search. S. Ghosh et al. examined search behaviors, users' perceived learning processes and outcomes under different levels of cognitive complexity in learning-related search tasks, and explored different behaviors related to learning [10]. Liu Chang et al., based on users' learning behaviors and processes during searching, revealed users' note-taking strategies and learning behavior characteristics by analyzing their information recording behaviors [11]. Regarding search behavior data collection, Liu Hanrui et al. suggested that considering the uniqueness of learning-related tasks, one could refer to the classification of search, reading, and recording behaviors and then refine the analysis of collaborative behaviors under each category [12]. Regarding future research prospects for learning-related search, Han Shuang et al. affirmed the importance of learning-related search research for improving retrieval systems and user experience [13].

Collaborative information search refers to "a series of activities in which a group or type of people identify and resolve shared information needs" [14].

In collaborative information search, scholars have primarily studied search behaviors, collaboration methods, collaboration experiences, and their influencing factors during the process; further, some scholars have explored differences between independent and collaborative search. Z. Yue et al. used a self-developed CollabSearch system to investigate the distribution and transition of user search behaviors during collaborative search [15]. Meanwhile, Z. Yue et al. compared query characteristics between collaborative and individual search in work and leisure task contexts, finding that queries in collaborative search were more diverse, with users employing more new and specialized queries [16]. C. Leeder et al. focused on collaborative information search behavior among university students in coursework contexts and compared search results, efficiency, and experiences between collaborative and single-user modes [17]. Zhang Lu et al. compared differences in search behaviors and experiences between collaborative and independent search based on a book interactive retrieval platform [9]. Subsequent research conducted more in-depth mining of user communication content and patterns during collaborative search, particularly the coding system designed for communication content, which provides insights for collaborative communication analysis [7]. Finally, regarding experimental platform selection, Zhang Min et al. focused on online tourism collaborative information retrieval, selecting the SearchTeam collaboration platform and allowing participants to communicate online [18], which provided methodological inspiration for this study.

Knowledge state change research has explored factors influencing knowledge state changes before and after searching and discussed methods for measuring knowledge state changes. C. Leeder and C. Shah' s research, set against the background of group learning projects, found through experiments that students' prior attitudes and experiences toward group assignments significantly affected search result quality [19]. J. Liu et al. focused on changes in searchers' topical knowledge levels during information task completion and found that task type affected knowledge levels and the degree of knowledge change [20]. N. Bhattacharya and J. Gwizdka explored the relationship between interaction variables, eye-tracking variables, knowledge state changes, and further extended this to the relationship between search effort and learning outcomes (i.e., knowledge state changes) in learning-related search [21]. Song Xiaoxuan et al. used user experiments to assess changes in users' knowledge levels before and after searching from both quantity and quality dimensions, providing a reference tool for evaluating learning outcomes in learning-related search [22]. L. Xu et al. explored various factors affecting knowledge state changes in collaborative search, finding that gender and age did not significantly affect user knowledge gains during collaborative web search; through a multiple linear regression model, they found that the interaction between users' education level and domain knowledge significantly affected knowledge gains, with users having low domain knowledge but higher education showing significantly greater knowledge gains than those without higher education [5]. Regarding knowledge state measurement methods, previous studies have tried mind maps (H. Liu et al.; C. Liu et al.) [23-24], objective questions (U. Gadiraju et al.) [25], subjective questions (Han Zhengbiao et al.) [26], and combined subjective-objective questions (K. Collins et al.) [27]. H. Liu et al. used mind maps to measure knowledge state, proposing a set of coding rules that could systematically characterize changes in participants' knowledge states and structures [24]. This method is easy to operate and aligns with this study' s research objectives; therefore, this study also adopts a mind map-based measurement and coding method.

Based on the literature review, this study proposes the following hypotheses:

H1: Groups with different prior knowledge level differences will show significant differences in collaborative search interaction behaviors.
H2: Groups with different prior knowledge level differences will show significant differences in collaborative experience.
H3: Groups with different prior knowledge level differences will show significant differences in post-search learning outcomes (i.e., knowledge state changes).

3 Research Method

This study employs the user experiment method, controlling for prior knowledge level differences among group participants to test the proposed hypotheses. This section introduces participant recruitment, experimental system selection, overall experimental procedure, and specific evaluation indicators and operationalization of independent and dependent variables.

3.1 Participant Recruitment and Experimental System Selection

This study recruited interested students from various Peking University departments through WeChat groups by distributing online questionnaires to preliminarily measure their prior knowledge levels and screen participants based on gender balance, department balance, and prior knowledge level differences. Ultimately, 24 students were recruited from the Information and Engineering Science Division, Social Sciences Division, and Humanities Division, including 11 males and 13 females. They were grouped into pairs based on prior knowledge levels, forming 12 groups: four "homogeneous high-level groups," four "heterogeneous groups," and four "homogeneous low-level groups." Specific grouping details are shown in .

** Grouping Based on Members' Prior Knowledge Levels**

During the experiment, two participants in each group came to the laboratory simultaneously, each using a computer with the Windows operating system. The entire search process was recorded using Windows' built-in screen recording function. Participants used the Chrome browser and Baidu search engine for searching. ProcessOn (https://www.processon.com/) was used as the collaboration platform. ProcessOn is an aggregation platform for online diagramming tools that supports creating mind maps, flowcharts, UI prototype diagrams, etc., and allows users to share their work with collaborators who can read, edit, and comment. In this experiment, we primarily used ProcessOn' s mind mapping function. The two participants in each experiment used two independent accounts to draw mind maps individually before each task and used the collaborative drawing function to jointly complete one mind map during the task.

3.2 Experimental Procedure and Search Task Design Before the experiment began, researchers introduced the experimental procedure to participants and helped them familiarize themselves with ProcessOn. Each group completed two tasks themed "artificial intelligence." Referencing L.W. Anderson et al.' s classification of cognition in learning: memory–understanding–application–analysis–evaluation–creation [28], this study removed the highest cognitive level (creation) and designed two task types: "comprehension" and "evaluation." Comprehension tasks are lower in cognitive hierarchy, requiring the process of "memory–understanding" ; evaluation tasks are higher in cognitive hierarchy, requiring "memory–understanding–application–analysis–evaluation." To better simulate real work tasks and conduct more comprehensive and scientific evaluations of collaborative search effectiveness, this study designed the experimental tasks as simulated work tasks [29]. During the experiment, users were provided with a simulated work task scenario to guide them in thinking about how to obtain useful information through interaction with collaborators and the system. Yue Linlin et al.' s research validated the effectiveness of using simulated work tasks as substitutes for real work tasks in information retrieval system evaluation and user information search behavior research [30]. Specific task contents are shown in .

** Search Task Details**

Before searching began, each participant read the requirements of the comprehension task and drew a mind map based on their own cognition using ProcessOn. After completing individual mind maps, the two participants in each group collaboratively completed the comprehension task, collaboratively searching for relevant information while jointly completing a mind map on ProcessOn. After task completion, a post-task questionnaire was distributed for self-assessment of collaborative experience, including task completion, task difficulty, task familiarity, search experience, and knowledge change. The two participants then completed the evaluation task following the same procedure. Since comprehension and evaluation tasks have a progressive relationship in cognitive complexity, this experiment did not rotate task order.

3.3 Independent Variable Assessment Indicators and Operationalization This study's independent variable is the different grouping methods based on prior knowledge level differences among group members, specifically including three grouping methods: "homogeneous low-level group," "heterogeneous group," and "homogeneous high-level group."

When measuring participants' prior knowledge levels, this study used self-assessment methods, including keyword self-assessment and comprehensive self-assessment. For keyword self-assessment, this study used "artificial intelligence" as the theme and selected 10 important keywords in the AI field (natural language processing, machine learning, pattern recognition, neural networks, complex systems, genetic algorithms, computer vision, facial recognition, data mining, strong/weak AI. Keywords were initially screened through a "red book" of translated terms compiled by the Machine Heart translation team, then reviewed by multiple senior students from the university' s Information Science and Technology College Intelligent Systems Department before final confirmation.), asking users to self-assess on a five-point scale. For comprehensive self-assessment, participants were directly asked about their overall understanding of artificial intelligence, also on a five-point scale. Each part had 11 items worth 5 points each, with a total of 55 points. Using 27.5 points as the cutoff, scores below indicated lower prior knowledge levels, and scores above indicated higher prior knowledge levels.

For grouping, this study referenced the educational concepts of "heterogeneous grouping" and "homogeneous grouping." Heterogeneous grouping refers to grouping 2-8 students with different academic performance, abilities, gender, personality, and family backgrounds into a cooperative group [31], while homogeneous grouping is the opposite. Generally, compared with homogeneous grouping, heterogeneous group members have certain complementarities that are conducive to mutual assistance and cooperation [32]. Therefore, this study paired participants based on prior knowledge levels "high-high," "low-low," and "high-low," dividing them into "homogeneous high-level," "homogeneous low-level," and "heterogeneous" groups. A t-test showed that the 12 participants with lower prior knowledge levels scored significantly higher than the 12 participants with higher prior knowledge levels ($t = -7.876$, $p < .000$).

3.4 Dependent Variable Assessment Indicators and Operationalization This study involves three key dependent variables: interaction behavior, collaborative experience, and knowledge state change.

3.4.1 Interaction Behavior

Regarding interaction behavior, this study focused on users' retrieval, browsing, and collaboration during collaborative search, selecting the indicators shown in to describe interaction behavior.

** Interaction Behavior Indicators and Operationalization**

3.4.2 Collaborative Experience

This study' s assessment of collaborative experience mainly included five dimensions: task completion, task difficulty, task familiarity, knowledge change degree, and search experience, all self-assessed on a five-point scale (gradually increasing from 1 to 5). Each item calculated the mean score of the two participants per group, and the five items were summed to form the collaborative experience score.

Regarding collaborative experience assessment, this study referenced previous scholars' definitions and analyses of user experience. For example, E.L.C. Law et al., through a survey report of 275 researchers and UX practitioners, identified several forms of user experience definitions and concluded that user experience has dynamic, context-dependent, and subjective characteristics [33]. Since user experience itself is subjective, using self-assessment to evaluate participants' collaborative experience is reasonable.

3.4.3 Knowledge State Change

Regarding knowledge state change, this study referenced Song Xiaoxuan et al.' s analytical framework, evaluating knowledge state changes from both quantity and quality dimensions [22]. For quantity, this study conducted quantitative analysis of group-level knowledge state growth from depth and breadth perspectives, with specific indicators including knowledge state maximum increment, knowledge depth average increment, and knowledge breadth increment. For quality, mind map node quality was assessed from three dimensions: knowledge relevance, user viewpoints, and knowledge analysis level. During quality assessment, two coders independently coded the three quality-related indicators, showing strong consistency (Kappa = .84). Disagreements were resolved by averaging the two coders' scores. The indicators for knowledge state change are shown in .

** Knowledge State Change Indicators and Operationalization**

It should be noted that the maximum level refers to the level of the smallest branch in the mind map. The calculation method for average level after level three is as follows:

Average level after level three = Sum of levels of all nodes after level three / Total number of thinking paths starting from level three nodes

[**Figure 1: see original paper**] shows an example mind map from participant No. 11 in the "heterogeneous-2" group drawn independently before searching.

4 Results

4.1 Effect of Prior Knowledge Differences on Search Interaction Behavior This study found that prior knowledge differences had no significant effect on search interaction behavior indicators. Using task type as a moderating variable, ANOVA was conducted on interaction behavior indicators. In evaluation task contexts, groups with different prior knowledge differences showed significant differences in average time spent viewing each content interface at the .01 significance level, as shown in .

In evaluation tasks, the homogeneous high-level group used significantly more search queries per capita than the homogeneous low-level group ($p < .001$); the heterogeneous group also used significantly more search queries per capita than the homogeneous low-level group ($p < .05$). Further examination of specific queries revealed that participants with high prior knowledge used more specific and professional search terms (e.g., "natural language generation,""deep learning transformer"), while participants with low prior knowledge mostly used terms mentioned in the task description (e.g., "AI development history," "facial payment"). Among the 12 participating groups, member contribution rates ranged from 0%-100%; contribution rate differences ranged from 2%-100%. No clear pattern emerged across groups regarding contribution rate differences. One-way ANOVA results showed no significant differences in collaborative contribution rate differences among the three group types ($F = .136$, $p = .874$).

4.2 Effect of Prior Knowledge Differences on Collaborative Experience Among collaborative experience indicators, homogeneous low-level groups scored highest on task completion, knowledge change degree, and search experience. shows the means of search experience across groups and Kruskal-Wallis test results. Analysis revealed significant differences among groups in task completion and knowledge change degree at the .05 significance level, while differences in other indicators were not statistically significant.

Post-hoc tests found that in task completion, homogeneous high-level and homogeneous low-level groups scored significantly higher than heterogeneous groups ($p < .05$). In knowledge change degree, homogeneous low-level and heterogeneous groups scored significantly higher than homogeneous high-level groups ($p < .05$). Thus, the three groups differed substantially in task completion and knowledge change degree experiences: homogeneous high-level groups rated both their task completion and knowledge change degree highly; homogeneous low-level groups rated their task completion high but knowledge change degree low; heterogeneous groups rated both their task completion and knowledge change degree low.

To exclude task type effects, separate Kruskal-Wallis tests were conducted for each task, revealing that differences in knowledge change degree among groups were manifested in evaluation tasks.

4.3 Effect of Prior Knowledge Differences on Knowledge State Change This study evaluated the degree of knowledge state change before and after collaborative search tasks from both knowledge quantity and quality dimensions.

4.3.1 Knowledge Quantity Change In terms of knowledge depth change, this study found that knowledge depth generally increased for all group members after collaborative search, both in maximum level expansion and average depth increase. Intuitively, homogeneous high-level groups had lower scores on both indicators. Further ANOVA on mean values of maximum change and average depth change found no significant differences among the three groups with different prior knowledge level differences. Using task type as a moderating variable, ANOVA on interaction behavior indicators found no significant differences in either task context. In summary, prior knowledge differences had no significant effect on knowledge depth change.

In terms of knowledge breadth change, using total mind map node count increment as the indicator, collaborative search generally increased knowledge breadth. ANOVA on mean values of post-level node count changes across groups showed significant differences among groups at the .05 significance level, as shown in . Specifically, homogeneous low-level groups added more total nodes than homogeneous high-level groups. This may be because homogeneous low-level groups initially lacked knowledge and had fewer mind map nodes, resulting in greater knowledge gains after searching, while homogeneous high-level groups already had relatively rich initial mind map nodes. Meanwhile, although heterogeneous groups had one member with low prior knowledge, the group' s knowledge breadth gain was not significantly different from homogeneous high-level groups.

4.3.2 Knowledge Quality Change In quality assessment, this study analyzed knowledge relevance, user viewpoints, and knowledge analysis level, with results shown in .

First, all three groups' mind map quality improved after searching. t-tests showed that homogeneous low-level groups' post-task mind maps improved significantly in knowledge relevance ($t = 4.65$, $p = .02$) and user viewpoints ($t = 4.70$, $p = .02$) compared to pre-task, with no significant change in knowledge analysis level. Heterogeneous groups showed significant improvement in knowledge relevance after searching ($t = 5.42$, $p = .01$). For homogeneous high-level groups, both knowledge relevance ($t = 4.735$, $p = .02$) and user viewpoints ($t = 5.00$, $p = .02$) improved significantly after tasks.

Second, comparing the three groups, Kruskal-Wallis tests before searching tasks showed that homogeneous high-level groups scored significantly higher than heterogeneous and homogeneous low-level groups in knowledge relevance ($^2 = 6.125$, $p = .05$). However, after searching tasks, no significant differences existed among the three groups. Finally, regarding pre-post increments, homogeneous low-level groups numerically outperformed the other two groups in knowledge relevance and user viewpoints. No statistically significant differences were found among the three groups in knowledge relevance, user viewpoints, or knowledge analysis level.

5 Discussion

This study designed a group collaborative search context through simulation tasks, recruited participants grouped by prior knowledge level differences, and examined search behaviors, experiences, and learning outcomes in collaborative contexts, attempting to provide insights for real-world collaborative grouping and search system optimization.

First, this study found that in collaborative search interaction behaviors, prior knowledge differences significantly affected the number of search queries. Specifically, groups with higher prior knowledge collaborators (including homogeneous high-level and heterogeneous groups) used significantly more search queries than homogeneous low-level groups. Additionally, those with high prior knowledge used more professional and specific search terms beyond those mentioned in task descriptions, while low prior knowledge users generally selected general keywords from task descriptions, resulting in more limited and less diverse queries.

Second, this study found that the three groups with different prior knowledge differences demonstrated distinct characteristics during collaborative search.

For heterogeneous groups, self-assessments of collaborative experience, task completion, and knowledge change degree were significantly lower than other groups. Meanwhile, in knowledge state changes, heterogeneous groups' knowledge breadth growth was lower than homogeneous low-level groups. Possible reasons include that large prior knowledge differences between the two members led to poor collaborative experience, dissatisfaction with task completion, which further affected search and learning outcomes, resulting in minimal knowledge state changes.

For homogeneous high-level groups, they had clear advantages in knowledge relevance before collaborative search tasks, but these advantages disappeared after task completion, and their knowledge quantity growth was significantly lower than homogeneous low-level groups. This may be because regardless of prior knowledge level, searchers could rely on search systems to acquire new knowledge, compensating for insufficient prior knowledge to some extent. However, from self-assessment of search effectiveness, homogeneous high-level groups rated their task completion significantly higher than heterogeneous groups and their knowledge change degree higher than other groups. This may be because both collaborators in homogeneous high-level groups had certain knowledge foundations and similar knowledge levels, making communication and decision-making smoother during collaboration, leading to higher self-assessment of task completion. Additionally, homogeneous high-level group members might more easily integrate newly acquired knowledge with their existing knowledge structures during search and collaboration, thereby promoting changes in their existing knowledge structures. The results also show that homogeneous high-level groups' perception of knowledge state changes was mainly reflected in evaluation tasks, where the two members' prior knowledge reserves might have focused more on "memory" or "understanding" levels, and evaluation tasks prompted deeper reflection and judgment of existing and newly acquired knowledge, with depth changes in knowledge state making them feel significant changes.

Homogeneous low-level groups showed significantly higher knowledge breadth growth than the other two groups, with higher self-assessment of task completion but lower self-assessment of knowledge change degree. This discrepancy may be because homogeneous low-level groups had little initial knowledge and could quickly add nodes to mind maps through searching, expanding knowledge breadth. However, learning involves not just information accumulation but also knowledge understanding and absorption, and brief searching may not enable users to develop deep understanding in unfamiliar domains, leading homogeneous low-level groups to perceive low knowledge change degree. Yet because both members had similar knowledge levels, communication was relatively smooth, making it easier to reach consensus on mind map modifications, resulting in higher satisfaction with task completion.

Regarding measuring contribution differences to collaborative outcomes, this study proposed the "collaborative contribution rate difference" indicator. Although no significant effect of prior knowledge differences on this indicator was found, future research could examine other factors such as participant personality, intimacy, or search ability differences to further verify what variables affect contribution differences in collaborative search.

In summary, this study found that the degree of explicit knowledge state change may not align with collaborators' self-perceived knowledge state change. Homogeneous high-level groups had the least knowledge breadth growth but perceived significant knowledge state changes; homogeneous low-level groups had the greatest knowledge quantity and quality improvements but perceived minimal knowledge state changes. This provides two insights: First, how should knowledge level change be measured in learning-related search? While mind mapping can externalize tacit knowledge, it may not reflect users' self-perception or their understanding and internalization of acquired information. Future research should explore differences between self-perception and objective knowledge state changes. Second, we cannot rely entirely on user self-assessment and must consider biases in collaborators' self-cognition.

6 Conclusion and Future Work

This study used the user experiment method to explore differences in interaction behaviors, collaborative experiences, and knowledge state changes among groups with different prior knowledge level differences. The main findings show that prior knowledge differences affect collaborative search primarily in collaboration and learning aspects. In collaboration, prior knowledge differences mainly affect collaborative search experience—specifically, homogeneous groups have better collaborative search experiences due to similar knowledge levels and smooth communication. In learning, prior knowledge level affects search behavior (high prior knowledge users employ richer, more professional, and specific queries for faster, more accurate information acquisition) and prior knowledge differences are reduced through searching, demonstrating that collaborative search can promote learning to compensate for insufficient prior knowledge.

Based on these findings, we propose the following recommendations for grouping and search system improvement in collaborative information search:

When grouping before collaborative search, "heterogeneous grouping" may not allow members with high prior knowledge to fully play mentoring roles because knowledge level differences may hinder collaboration. Grouping students with similar prior knowledge levels facilitates better communication and collaborative experiences.

During collaborative search, search terms from high prior knowledge users can serve as important basis for system-recommended keywords. The system could directly reuse high prior knowledge users' queries as recommended terms to help low prior knowledge users determine search terms. Additionally, the system could use sub-concepts of group members' queries as recommended terms to help low prior knowledge users search more specifically and deeply.

Different support should be provided to learners with different prior knowledge levels. For high prior knowledge learners, tasks with higher cognitive levels (analysis, evaluation, creation) can be assigned to promote reflection on existing foundational knowledge.

This study has limitations: knowledge state change was measured at the group level; future research could examine individual knowledge state changes in greater detail. Although the entire experiment was screen-recorded and audio-recorded, only interaction behaviors and collaborative experience data were analyzed. Previous research has analyzed contextual data such as participants' chat content in collaborative information search [34]. Future research could utilize such contextual data for more detailed analysis of collaborative information search processes.

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Author Contributions

Jiang Xue: Responsible for writing the results, discussion, conclusion, and future work sections; assisted in writing the research method section.
Li Yujia: Responsible for writing the overview, research method, and results sections; assisted in writing the discussion section.
Zhang Yuanzhe: Responsible for writing the literature review and results sections; assisted in writing the discussion section.
Liu Chang: Provided research guidance and paper revision.

Note: Figure translations are in progress. See original paper for figures.