Effects of Task Type and Cognitive Learning Strategies on Video Search Behavior in Self-Regulated Learning Contexts: Postprint

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Abstract

[Purpose/Significance] Video platforms have emerged as a new knowledge learning scenario in the Internet era. In this context, the search interaction process can be viewed as a self-regulated learning process. This study focuses on investigating the influence of different task types and learning cognitive strategies on video-based search behavior within self-regulated learning contexts, aiming to enrich research on video-based search behavior in learning scenarios within the field of interactive information retrieval. [Method/Process] Two task types were selected: factual and skill-based. Cognitive strategies were categorized into four types based on the self-regulated learning framework: rehearsal, elaboration, organization, and critical thinking. The study employed an experimental method, using the Bilibili video platform as the test system. By adopting an existing measurement framework and based on experimental data, it explores differences in behavioral characteristics and search performance among users with different learning cognitive strategies when performing different types of tasks. [Results/Conclusion] The findings indicate that different task types and learning cognitive strategies influence search behavior and learning outcomes, showing significant differences across multiple metrics. By analyzing and summarizing the characteristics of tasks and cognitive strategies, this study proposes improvement suggestions for the system design of video-based search platforms in learning contexts, which holds positive significance for enhancing such search platforms and improving user search experience and learning efficiency.

Full Text

The Effects of Task Type and Learning Cognitive Strategies on Video-Based Search Behavior in a Self-Regulated Learning Context

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Abstract: [**Purpose/Significance**] In the Internet era, video platforms have become a new knowledge learning scenario. In this context, the search interaction process can be viewed as a self-regulated learning process. This study focuses on the effects of different task types and learning cognitive strategies on video-based search behavior in self-regulated learning contexts, aiming to complement research on video search behavior in learning scenarios within the interactive information retrieval field. [**Method/Process**] We selected two task types: factual and skill-based. Cognitive strategies were classified into four types based on the self-regulated learning framework: rehearsal, elaboration, organization, and critical thinking. The study adopted an experimental approach, using the Bilibili video website as the test system and borrowing existing measurement frameworks to explore differences in behavioral characteristics and search effectiveness among users with different learning cognitive strategies when performing different types of tasks, based on experimental data. [**Result/Conclusion**] The findings indicate that different task types and learning cognitive strategies affect search behavior and learning outcomes, showing significant differences across multiple indicators. By analyzing and summarizing these results in combination with task and cognitive strategy characteristics, we propose improvement suggestions for the use of video search platforms in learning contexts. These recommendations have positive implications for enhancing such search platforms and improving user search experience and learning efficiency.

Keywords: video search; self-regulated learning; task types; learning cognitive strategies; interactive information retrieval
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Introduction

In the Internet era, people' s demand for knowledge acquisition continues to grow, access channels are becoming increasingly diverse, and knowledge dissemination is showing a fragmented trend. How to leverage Internet tools to improve knowledge acquisition efficiency and encourage knowledge creation and learning are research directions for many Internet platforms and academic institutions, attracting numerous innovations. The latest "2020 China Online Audio-Visual Development Research Report" shows that as of June 2020, the scale of China's online audio-visual users exceeded 900 million, with a usage rate of 95.8% among netizens. According to expert surveys on industry development trends, 75.3% of people are more optimistic about the "online audio-visual + education" combination [1]. Video has changed traditional learning methods, with more users choosing to use Internet videos for learning, making video platforms a new knowledge learning scenario. The 2020 pandemic stimulated user attention and demand for knowledge-based video content. According to iResearch' s "2020 China Mobile Internet Content Ecology Insight Report," after the pandemic, audience attention to serious content such as science documentaries and news facts increased significantly, with an average growth rate of 16.7%. Lifestyle-oriented content also grew, while entertainment content saw a slight decline [2].

The concept of Self-Regulated Learning (SRL) was first proposed by B.J. Zimmerman et al. [3] in 1986. Self-regulated learning refers to the process by which learners activate and maintain their own thoughts, feelings, and behaviors, systematically directing them toward achieving learning goals [4]. Searching for knowledge-based videos typically involves users setting their own learning objectives. S.Y. Rieh et al. [5] believe that learning-oriented search is not just simple searching but also involves critically finding, evaluating, and using information for various search tasks. In this scenario, the search interaction process can be viewed as a self-regulated learning process. Learning objectives and self-regulated learning strategies are important components of self-regulated learning [6]. In experimental settings, we consider designing different types of search tasks to define different learning objectives for participants. Self-regulated learning strategies refer to learners' selection of appropriate methods to obtain information and skills. In P.R. Pintrich et al.' s framework [7], these are divided into three categories: cognitive strategies, metacognitive self-regulation strategies, and resource management strategies. Metacognitive self-regulation strategies emphasize the regulation of the learning process, resource management strategies emphasize the management of information resources, and cognitive strategies involve the selection of learning methods, making them more suitable for studying learning behaviors that emerge in video-based search from a holistic perspective.

Therefore, this study focuses on the effects of different task types and learning cognitive strategies on video-based search behavior in self-regulated learning contexts. Regarding learning-oriented search research, current studies mainly focus on comprehensive retrieval systems and domain-specific text retrieval systems, basically based on web or text content search and learning [8-10], lacking research on knowledge-based videos. Research on video learning behavior typically involves education scholars analyzing and mining online learning log data, mainly focusing on learners' autonomous learning behavior with course videos, with little attention paid to video information search behavior. The 2017 Dagstuhl Seminar proposed future research questions for learning-oriented search, including the relationship between learning processes and learning contexts, and how to draw on education-related theories to study search interaction processes [12]. Therefore, using the educational psychology concept of "self-regulated learning context" in this research has great innovative value, and treating learning cognitive strategies as an independent variable is also a new entry point. Additionally, with the vigorous development of online learning and education industries, exploring the factors influencing learners' search behavior has positive implications for promoting industry development.

Overall, studying the effects of different task types and learning cognitive strategies on video-based search behavior in self-regulated learning contexts helps fill the gap in current research on video-based search behavior in learning scenarios, represents a new contribution to the interactive information retrieval field, and provides new research ideas for studying video-based learning information search behavior.

Thus, this study attempts to explore and answer the following questions in a self-regulated learning context: (1) How do task type and learning cognitive strategies affect users' video-based search behavior and learning behavior? (2) How do task type and learning cognitive strategies affect users' video-based search effectiveness?

Literature Review

We searched Chinese academic databases (CNKI, Wanfang) using the Chinese search string SU=("video" OR "image") AND ("user" OR "student" OR "learner") AND ("search" OR "retrieve" OR "query" OR "find") AND ("behavior"), and English academic databases (Web of Science, EBSCO) using the English search string TS=((video* OR picture*) AND (user* OR student* OR learner*) AND (search* OR retriev* OR seek*)) to find literature from the past five years. We expanded the literature collection through snowballing based on citation relationships and finally selected 20 studies related to video search behavior after carefully reading abstracts and research content.

2.1 Characteristics of Video Search Behavior

With the rapid increase of video resources on the Internet, research on video search behavior has gradually emerged. For learning scenarios using video, Wang Hongjiang et al.' s research shows that most learners can maintain high attention levels in the first 3 minutes, and online learning videos of 6-9 minutes have relatively high learning effectiveness [11]. S. Dodson et al. found that learners exhibit two behaviors when actively watching videos: seeking (mainly dragging the progress bar) and highlighting (mainly note-taking) [13]. Additionally, X. Xie et al. found that users' attention allocation mechanisms on search result pages exhibit new features such as middle preference, slow decay, and line skipping when studying image search behavior, noting that video search, with its similar results presentation style to image search, likely shares similar user characteristics [14].

Regarding video resource relevance judgment, Wang Zhihong et al.' s research shows that topicality, scope, and authority affect users' video relevance judgments, with gender, information search ability, and topic familiarity having moderating effects [15]. S. Albassam et al. found that users' relevance judgment criteria in leisure contexts can be divided into eight dimensions: video content, participants' existing experience and background, participants' beliefs and preferences or situations, video source quality, video accessibility, other information in the environment, others' opinions, and video site recommendations, with video content being the most important criterion [16]. Their 2020 follow-up study showed that relevance judgments also change dynamically with search stages [17]. Overall, current domestic and international research on video resource search behavior is in its infancy, with even fewer studies on large Chinese video platforms.

2.2 Factors Influencing Video Search Behavior

Since current research on video search behavior is limited, this paper mainly summarizes influencing factors from general information resource search behavior studies as foundational support for the research design. Task type is an important influencing factor in user search processes. Zhao Mengju et al.' s image search experiments showed that more specific tasks lead to more casual user search behavior, while more subjective tasks lead users to more actively adjust their behavior, with the former having higher search satisfaction than the latter [18]. Yuan Hong et al., using log analysis and search process video analysis, found that task type significantly affects exploratory search behavior: the more complex the task, the more types of search tools used, the more users tend to use query expansion methods, and the deeper the link depth of web browsing [8]. K. Urgo et al., based on D. Anderson and D. Krathwohl' s classification system for learning, divided search tasks according to two dimensions—cognitive process and knowledge type—with cognitive processes including application, evaluation, and creation, and knowledge types including factual, conceptual, and procedural. Their experimental results showed that knowledge type has stronger effects than cognitive process, with conceptual tasks being perceived as most difficult and requiring more search behavior [19]. S. Ghosh et al. studied search tasks with different cognitive complexities and found that task cognitive complexity affects query length, is significantly positively correlated with users' topic interest and task difficulty ratings, and significantly negatively correlated with perceived helpfulness of prior knowledge [20].

Additionally, users' cognitive styles significantly affect search behavior. The concept of cognitive style was proposed by psychologist G.S. Klein to refer to an individual' s internal pattern of thinking, perceiving, and adapting to the external world [21]. Influenced by psychology research, information behavior studies frequently use Riding et al.' s holistic-analytic framework, among which Witkin et al.' s field independence-field dependence has been widely applied [22]. For example, Liu Hanrui et al.' s research shows that cognitive style has main effects on search behavior, with significant differences between participants with different cognitive styles in number of queries and total dwell time on search engine results pages (SERP). Analytic participants input more queries than holistic participants and have longer total dwell time on SERP, with cognitive style and topic familiarity showing interactive effects on SERP utilization and average note-taking time [9]. Sun Xiaoning et al. found that cognitive style affects reading engagement and note-taking engagement, with field-independent users more easily obtaining information from SERP titles, tending to read more content pages and record information promptly, while field-dependent users show the opposite pattern [10].

It should be noted that although many studies on cognitive style factors affecting search behavior have emerged in recent years, most use classic psychological tests for general individual cognitive styles. In learning-oriented search, individuals' primary goal is to acquire and absorb new knowledge, which may present different cognitive patterns than daily life. Therefore, this study uses the Motivated Strategies for Learning Questionnaire [7] from educational psychology to obtain individuals' cognitive strategy tendencies in self-regulated learning contexts, studying from an angle more aligned with learning-oriented search scenarios.

Research Methods

3.1 Test System Introduction

Major domestic and international video websites include Tencent Video, iQiyi, YouTube, and Netflix. Among them, Bilibili (https://www.bilibili.com/, hereafter referred to as "Bilibili") is the earliest video platform to emerge in knowledge-based videos and currently has the highest reserve of knowledge-based video content in China. On June 5, 2019, Bilibili launched the "Knowledge Zone" as a top-level category. That year, over 86 million people studied on Bilibili, equivalent to eight times the number of college entrance examination candidates in the same year. The number of knowledge-focused content creators (UP 主) increased by 151% year-over-year, and learning video views increased by 274% [23]. Therefore, Bilibili can be regarded as representative of knowledge-based video platforms, and we selected it as our test system.

3.2 Research Design

3.2.1 Experimental Overview This study adopted an experimental approach to explore whether users with different learning cognitive strategies exhibit behavioral characteristics and search effectiveness differences when performing different types of video-based search tasks.

Video-based learning search tasks in this study have certain difficulty, requiring participants with adequate learning capabilities. Due to the difficulty of search experiments, achieving large sample sizes is challenging. In existing studies using search experiments as the primary method, participant numbers typically range from a dozen to several dozen. For example, D. Hawking et al. [24] and

F. Can et al. [25] selected 6 and 19 participants respectively to evaluate search efficiency, while Yuan Hong et al. [8] recruited 24 participants for exploratory search experiments. Video search experiments involve many processes and are time-consuming. Considering experimental costs and feasibility, this study ultimately recruited 12 undergraduate students from Peking University, including 2 males and 10 females, all from the Department of Information Management and in lower undergraduate years (11 first-year students and 1 second-year student). To minimize interference from network data changes, all experiments were conducted intensively on December 12-13, 2020.

We recorded users' search interaction behaviors through screen recording using Bandicam software (https://www.bandicam.cn/, a high-definition video recording tool that can record all on-screen operations and mouse clicks).

3.2.2 Sample Selection We controlled for variables including department, grade, system usage experience, and knowledge level. First, we limited participants to lower-year undergraduates from Peking University' s Department of Information Management (primarily first-year students) to ensure similar professional capabilities and knowledge structures. We excluded both novice and expert users, selecting participants who occasionally or sometimes used video search for learning to ensure similar experience levels. Second, we chose participants who were completely unfamiliar or basically unfamiliar with factual task topics and who had never used or only used a few times (but were not proficient with) the software involved in skill-based tasks, ensuring that the information and knowledge needed to complete tasks originated from the experimental search process.

Learning cognitive strategies are divided into four dimensions: rehearsal, elaboration, organization, and critical thinking [7]. Based on P.R. Pintrich' s definitions of these four dimensions, we translated them as follows: (1) **Rehearsal**: Basic rehearsal strategies mainly refer to memorizing key points of learning content, most commonly used for simple learning tasks that primarily activate learners' working memory rather than create new long-term memory. (2) **Elaboration**: Elaboration strategies include paraphrasing, summarizing, analogizing, note-taking, etc., helping learners establish connections between concepts and transform learning content into long-term memory. (3) **Organization**: Organization strategies include classification, outlining, summarizing key points, etc., helping learners filter effective information and establish connections between learning content. (4) **Critical Thinking**: Critical thinking refers to learners applying previously acquired knowledge to new situations to better solve problems, make decisions, or critically evaluate learning content.

We measured cognitive strategies using the Motivated Strategies for Learning Questionnaire (MSLQ), referencing the simplified Chinese translation version from previous research [26]. The questionnaire used a seven-point Likert scale to measure participants' use of the four cognitive strategies, with scores ranging from 1 to 7 for each strategy. To ensure representative experimental samples, after excluding unqualified samples, we selected participants whose scores on the four dimensions fell in the top 25% and bottom 25% of the overall distribution, removing duplicates to finally select 12 participants.

[Figure 1: see original paper] shows the distribution of participants' standardized scores across the four dimensions. The overall score range for the rehearsal dimension was 3.67-7, with the top 25% (6.67-7) representing high rehearsal ability samples and the bottom 25% (3.67-4.67) representing low rehearsal ability samples. The elaboration dimension range was 2-7, with the top 25% (6-7) as high elaboration ability and bottom 25% (2-4) as low elaboration ability. The organization dimension range was 1-6.67, with the top 25% (5.33-6.67) as high organization ability and bottom 25% (1-3.67) as low organization ability. The critical thinking dimension range was 2.25-6, with the top 25% (5.25-6) as high critical thinking ability and bottom 25% (2.25-3.75) as low critical thinking ability.

According to Q.H. Mazumder' s 2014 cross-cultural comparison study [27], the overall score range was 1-7, with Chinese student sample standardized mean scores of 4.38, 4.43, 4.81, and 4.59 for the four dimensions respectively. Our selected high- and low-ability samples were basically distributed on both sides of these means, making them largely representative.

3.2.3 Experimental Tasks In D.R. Krathwohl' s analysis framework for learning objectives, knowledge is divided into four types: factual knowledge, conceptual knowledge, procedural knowledge, and metacognitive knowledge [28]. Factual knowledge refers to basic elements learners must know to solve problems; procedural knowledge refers to sets of procedures or steps for how to do things, used when learning skills and reproducing operational processes. In knowledge-based videos, factual and procedural knowledge appear frequently and have high learning demand. Therefore, this study selected factual and procedural knowledge as learning objects, designing two task types: (1) **Factual Information Search Task (Fact-Finding, FF)**: Examining factual knowledge points, searching for specific, concrete facts and information. (2) **Skill-Based Information Search Task (Skill-Using, SU)**: Examining participants' understanding of tasks and mastery of skill operation processes.

Each task type included two search tasks with different topics, totaling four search tasks:

- **FF-1**: Selecting a good stock requires comprehensive consideration of many factors, two important ones being P/E ratio and P/B ratio. Please search for: (1) the calculation method of P/B ratio; (2) types and calculation methods of P/E ratio; (3) a brief understanding of applicable scenarios for both indicators.
- **FF-2**: The brain is the most important structure of the central nervous system. Please use Bilibili to search for relevant videos to learn about the divisions of the cerebral cortex and the main functions of each division,

then answer [Figure 2: see original paper] with the names of the four brain divisions (in Chinese or English) and match the four divisions with their functions.

- **SU-1**: Using data visualization software for data analysis is a very practical skill. Tableau is one of the most popular commercial data visualization software. Please search for relevant videos on Bilibili, learn, and use Tableau to reproduce the chart shown in [Figure 3: see original paper].
- **SU-2**: PS (Photoshop) is commonly used software in image editing. Please search for how to use PS to turn [Figure 4: see original paper] into a sketch effect.

Note: Image source: http://picjumbo.com/page/5/

For the single factor of task type (FF and SU), we used a Latin square within-subjects rotation design to control for task order effects.

3.2.4 Experimental Procedure The experiment involved 12 participants, each completing four search tasks. After manual inspection and removal of invalid search sessions, we obtained 45 valid search sessions.

The experimental procedure was as follows: 1. Participants completed a pre-test questionnaire including personal background information, knowledge background tests related to search tasks, and the learning strategies scale to assess topic familiarity and learning strategy types. 2. Participants were invited to a closed laboratory environment to use the same desktop computer for the experiment. 3. Participants received experimental training about the procedure and requirements, then performed free searches on Bilibili with grid-style result presentation. 4. The experiment consisted of four independent search tasks. For each task, participants first read the search task, then began searching without time limits. They could record useful information in a Word document and complete the task based on searched information. When participants believed they had completed the task, the current task ended. 5. After each search task, participants closed the browser and Word document, then completed a task evaluation questionnaire assessing current knowledge level, search difficulty, and learning difficulty. 6. After completing the task evaluation questionnaire, participants proceeded to the next search task, repeating the steps until all four tasks were completed. 7. After all search tasks, participants completed a post-test questionnaire. 8. Task completion order was arranged using a Latin square matrix to avoid experimental errors from task sequence.

3.3 Experimental Variables

3.3.1 Interaction Behavior Variables (1) Search Behavior. Our analysis of video search behavior focused on search strategies and search result lists, developing 10 indicators based on these two aspects, summarized in .

(2) Learning Behavior. We defined learning behavior as user interaction actions on video content pages, reflecting stages of knowledge discovery, acquisition, filtering, and learning. Combining video learning characteristics, we developed nine indicators from overall situation and specific operations, summarized in .

The entire user operation process was recorded as video through screen recording software, making all variables measurable through video records.

3.3.2 Effectiveness Evaluation Variables We evaluated post-search learning effects from three aspects: user evaluation of search system functionality, user self-evaluation of search learning process, and objective evaluation of learning effects.

(1) User Evaluation of Search System Functionality. We assessed system usability and system learnability using the SUS (Software Usability Scale) [31] in the post-test questionnaire.

(2) User Self-Evaluation of Search Learning Process. Participants evaluated search strategy satisfaction, task completion difficulty, and post-experiment knowledge level. Task completion difficulty was measured after each search task using a task evaluation questionnaire adapted from S. Ghosh et al. [20], covering both search and learning processes. Search strategy satisfaction was measured using the post-test questionnaire, and post-experiment knowledge level was measured using the post-test questionnaire and compared with pre-experiment knowledge level from the pre-test questionnaire, with the difference representing knowledge gained during the experiment.

(3) Objective Evaluation of Learning Effects. J.R. Hackman [32] defined Task Autonomy as having substantial freedom, independence, and discretion in task design, such as coordinating specific work and determining task processes. The measurement of custom task completion effectiveness depends partly on designers' motivations, purposes, and expected outcomes [33]. D. Kriksčiūnienė et al. [34] noted that when evaluating team task performance, both team members and task completion effectiveness should be considered: team members' professional capabilities, knowledge structure, and experience level, and task characteristics, difficulty, answer clarity, organizational framework, and format.

Since our participants were basically from the same grade and major with highly consistent professional knowledge and learning experience, this study comprehensively considered task characteristics and question design motivations, providing different scoring standards for the two task types. Factual tasks emphasize information comprehensiveness, completeness, and specificity, so we graded answers based on problem matching degree and completeness. Skill-based tasks emphasize operational process accuracy and result consistency, so we used key steps in the implementation process and main effects as scoring criteria.

We retained participants' final answer data, with a full score of 100. Tasks were divided into sub-tasks with assigned points of 5, 10, 20, 30, and 40. Using pre-established uniform standards, we evaluated and scored each participant' s task completion effectiveness, with answer data scores representing learning effects for objective measurement.

We also used total task completion time as an evaluation indicator. Learning efficiency was calculated as:

Learning Efficiency = Learning Effect / Task Completion Time (Formula 1)

This means users achieving better learning effects in shorter time have higher learning efficiency.

Test Results

4.1 Analysis of Factors Influencing User Interaction Behavior

4.1.1 Effects of Task Type on User Interaction Behavior Normality tests indicated that variable distributions basically met normal distribution assumptions. We used ANOVA to analyze task type effects on user interaction behavior, with results shown in , [Figure 5: see original paper], and .

In search behavior (see), task type differences mainly manifested in search strategies. Factual tasks had significantly longer average query length than skill-based tasks ($p = 0.041 < 0.05$). Screen recordings showed participants could extract keywords from given tasks to construct queries, but different task types affected initial query construction. For factual tasks, participants directly input specific task descriptions, such as "stock P/B ratio." For skill-based tasks, participants tended to first search for software/platform tutorials, such as searching "Tableau" rather than combining "Tableau" and "bar chart" initially, only expanding queries after the first search failed to meet needs. We speculate that the lack of specific task context description in skill-based tasks' initial searches led to relatively shorter average query lengths.

In learning behavior (see), task type significantly affected repeated video viewing times, deep viewing video quantity, and pause times. Factual tasks showed significantly more repeated video viewing ($p = 0.048 < 0.05$) and deep viewing video quantity ($p = 0.036 < 0.05$) but significantly fewer pause times ($p = 0.049 < 0.05$) than skill-based tasks. Repeated viewing and deep viewing (watching >50% duration) both reflect users'deep learning behaviors with video knowledge, indicating that participants explored video content more deeply when completing factual tasks. Combined with screen recordings and related data, videos clicked in factual tasks had significantly shorter average durations than those in skill-based tasks. Short videos generally impose lower time and cognitive costs than long videos, making it easier for participants to repeatedly view and deeply learn videos related to factual tasks. Fewer participants had patience for long software/platform training videos in skill-based tasks, often accompanied by speeding up playback and dragging the progress bar.

4.1.2 Effects of Cognitive Strategies on User Interaction Behavior We used Spearman correlation coefficients to analyze relationships between cognitive strategies and search behavior/learning behavior variables, with results shown in and .

In search behavior (see), participants' rehearsal ability showed significant negative correlation with number of different queries used ($r = -0.416$, $p = 0.043 < 0.05$), meaning participants better at rehearsal used fewer different queries. Conversely, critical thinking ability showed significant positive correlation with number of different queries ($r = 0.407$, $p = 0.049 < 0.05$) and repeated queries ($r = 0.487$, $p = 0.016 < 0.05$), meaning participants better at critical thinking tended to try constructing different queries multiple times and repeatedly check results of previously searched queries. Additionally, rehearsal ability showed significant positive correlation with average mouse hover times ($r = 0.478$, $p = 0.018 < 0.05$), while organization ability showed significant positive correlation with total mouse hover times ($r = 0.410$, $p = 0.046 < 0.05$). Mouse hovering is a distinctive Bilibili feature, indicating participants consciously previewed video content before clicking. Screen recordings showed not all participants clicked on hovered results, suggesting hovering may represent a higher-level active filtering strategy. Data analysis indicates participants with stronger rehearsal and organization abilities are more inclined to conduct preliminary content judgment and filtering of videos on search result pages.

In learning behavior (see), participants' rehearsal ability showed significant negative correlation with repeated video viewing times ($r = -0.420$, $p = 0.041 < 0.05$), elaboration ability showed significant positive correlation with video pause times ($r = 0.494$, $p = 0.014 < 0.05$), while organization and critical thinking abilities showed no significant correlation with learning behaviors. Results indicate participants with stronger rehearsal ability are less inclined to repeatedly watch videos, while those with weaker rehearsal ability tend to repeatedly watch certain videos to consolidate memory. Additionally, participants with stronger elaboration ability tend to pause videos during learning.

4.2 Analysis of Factors Influencing User Search Effectiveness

4.2.1 Effects of Task Type on User Search Effectiveness t-test results showed task type significantly affected perceived learning difficulty ($p = 0.031 < 0.05$), learning effectiveness ($p = 0.001 < 0.01$), total task completion time ($p = 0.002 < 0.01$), and learning efficiency ($p = 0.009 < 0.01$). Cohen' s d values were all greater than the critical point of 0.80, indicating large differences (see and [Figure 6: see original paper]).

From user self-evaluation, learning difficulty reflected users' assessment of difficulty in understanding task-related knowledge and answering questions. For participants, skill-based tasks were significantly more difficult than factual tasks.

From objective effectiveness, factual tasks generally achieved better learning effects, took less time, and showed significantly higher learning efficiency than skill-based tasks. Analyzing task characteristics, this aligns with expectations: factual tasks only involve finding facts, concepts, and propositions, while skill-based tasks require actual operation, internalizing video steps into procedural knowledge, and typically have no unified answers, making them more difficult for novice users unfamiliar with relevant software/platforms. In skill-based tasks, participants struggled to find videos directly corresponding to tasks, requiring multiple searches, filtering, and attempts, which was time-consuming. Even when perfectly imitating video steps, various problems arose in actual operation due to inconsistent environment configurations and unfamiliarity with software, making it difficult to achieve satisfactory final results.

4.2.2 Effects of Cognitive Strategies on User Search Effectiveness As shown in , critical thinking ability showed correlations with multiple effectiveness indicators. At the 95% confidence level, critical thinking ability was significantly positively correlated with overall system evaluation, system usability, search strategy satisfaction, and learning difficulty evaluation.

Based on previous correlation analysis between cognitive strategies and search behavior, critical thinking was significantly correlated with repeated query numbers. Considering that participants' evaluations of search systems and their own search learning processes were made after the experiment and influenced by cognitive patterns, we hypothesized that critical thinking ability moderates the effects of repeated query numbers on overall system evaluation, system usability, search strategy satisfaction, and learning difficulty.

Moderation test results are shown in . At the 95% confidence level, the interaction term between critical thinking and repeated query numbers was significant for overall system evaluation, system usability, and search strategy satisfaction, with significant ΔF changes after adding the interaction term. This means that when repeated query numbers affect these evaluations, the moderating variable critical thinking shows significantly different effect magnitudes at different levels—specifically, the effect magnitude is greater when critical thinking ability is stronger. However, critical thinking did not moderate perceived learning difficulty.

Discussion and Conclusion

Based on self-regulated learning theory, this study used user experiments to explore the effects of different task types and learning cognitive strategies on video-based search behavior in self-regulated learning contexts, complementing research in the interactive information retrieval field. The experiment selected two task types (factual and skill-based) and four cognitive strategy types (rehearsal, elaboration, organization, and critical thinking) based on the self-regulated learning framework. Using Bilibili as the test system and borrowing existing measurement frameworks, we explored differences in behavioral characteristics and search effectiveness among users with different learning cognitive strategies when performing different tasks. Statistical analysis of experimental data yielded four main findings:

1. **Task type affects user search and learning behavior.** For search behavior, factual tasks had significantly longer average query length than skill-based tasks. When completing factual tasks, participants directly input specific task descriptions; for skill-based tasks, they tended to first search for software/platform tutorials, causing the length difference. For learning behavior, factual tasks showed significantly more repeated video viewing and deep viewing video quantity but significantly fewer pause times, indicating participants engaged in deeper learning for factual tasks but easily lost patience with skill-based tasks.

2. **Cognitive strategies affect user search and learning behavior.** For search behavior, rehearsal ability showed significant negative correlation with number of different queries used, while critical thinking ability showed significant positive correlation with number of different queries and repeated queries. Additionally, rehearsal ability showed significant positive correlation with average mouse hover times, and organization ability with total mouse hover times, suggesting participants with stronger rehearsal and organization abilities prefer preliminary content judgment and filtering of search results. For learning behavior, rehearsal ability showed significant negative correlation with repeated video viewing times, and elaboration ability showed significant positive correlation with pause times, while organization and critical thinking abilities showed no significant correlation with learning behaviors. Participants with stronger rehearsal ability are less inclined to repeatedly watch videos, while those with weaker rehearsal ability tend to repeatedly watch certain videos to consolidate memory. Participants with stronger elaboration ability tend to pause videos during learning. Screen recordings showed that in knowledge-based tasks, participants paused at key knowledge points, opened documents, and tried to describe key points in their own words as answers, while in skill-based tasks, they paused to try software operations, reflecting the core of elaboration strategies—building connections between concepts learned before and after.

3. **Task type affects video search effectiveness.** Both user self-evaluation and objective answer scores indicated that factual tasks achieved better learning effects, took less time, and showed significantly higher learning efficiency than skill-based tasks. Analyzing task characteristics, factual tasks only involve finding facts, concepts, and propositions, while skill-based tasks require actual operation, internalizing video steps into procedural knowledge, and typically have no unified answers, making them more difficult for novice users unfamiliar with relevant software/platforms. In skill-based tasks, participants struggled to find directly corresponding videos, requiring multiple searches, filtering, and attempts, which was time-consuming. Even when perfectly imitating

video steps, various problems arose in actual operation due to inconsistent environment configurations and unfamiliarity with software, making it difficult to achieve satisfactory final results.

4. **Cognitive strategies affect video search effectiveness.** Critical thinking ability showed correlations with multiple effectiveness indicators and played a moderating role in the effects of repeated query numbers on overall system evaluation, system usability, search strategy satisfaction, and learning difficulty. When critical thinking ability was stronger, the effect magnitude was greater. Participants better at critical thinking tend to try constructing different queries multiple times and repeatedly check previously searched query results, but critical thinking focuses more on playing a moderating role in the process of decomposing and completing tasks, making it difficult to moderate task difficulty perception. Therefore, for video-based information resources, different users' learning cognitive strategies should be considered, and targeted functional assistance matching their cognitive characteristics should be provided to improve user experience and learning effectiveness.

Based on these discussions, we propose the following recommendations for learning video platforms like Bilibili' s Knowledge Zone:

1. **Platform can build predictive models for task types and learning strategies** based on user search behaviors like query construction length, interaction behaviors like mouse hovering, and learning behaviors like repeated viewing, to label and differentiate different user types and provide personalized services. For users with strong critical thinking and organization abilities, the platform can track search frequency and reduce result order changes caused by synonym adjustments in search results to improve user confidence. For users with strong elaboration ability who tend to pause videos to build content connections, and users with weak rehearsal ability who tend to repeatedly watch videos, the platform can clearly mark video nodes where these types of users frequently pause and repeatedly watch.

2. **Platforms can process video data according to different user cognitive strategies and learning characteristics.** For users with strong critical thinking and organization abilities, platforms can use their search strategies to supplement and improve retrieval databases and synonym tables. For users with strong elaboration ability who pause videos to build content connections, platforms can learn their pause node patterns to assist in labeling key video nodes, and similarly for users with weak rehearsal ability who repeatedly watch videos.

3. **Platforms can adjust search result ranking strategies based on learning task types.** When users search for skill-based tasks, learning video platforms can assign higher weights to systematic, coherent teaching video collections in search results pages. When users search for knowledge-

based tasks, platforms can give higher weights to popular science introduction videos in relevant fields.

4. **Video learning websites can adjust functions** such as adding picture-in-picture mode reminders, refining Knowledge Zone video tag granularity, and strengthening note-taking, annotation, and other learning feedback functions to improve user learning efficiency. Since participants frequently switched between pages without using picture-in-picture functions, platforms can proactively provide detailed user help for Knowledge Zone features, such as reminding users about desktop picture-in-picture mode and note-taking functions, to help users make fuller use of features and improve search efficiency. Since users dragged progress bars frequently during learning video searches, platforms can consider refining Knowledge Zone video tag granularity to help users quickly understand video content and locate knowledge points, improving video search and learning efficiency. Learning video platforms can highlight functional features that differentiate them from other video platforms, strengthening interactive operations like note-taking and tagging, as well as communication and feedback functions, to optimize user experience and improve learning efficiency.

This study has limitations: (1) Sample selection: small sample size concentrated on lower-year undergraduates from Peking University' s Department of Information Management, limiting generalizability. (2) Data collection: manual statistics from screen recordings may have timing deviations for duration-related variables; more optimized collection methods need exploration. (3) Data analysis: we analyzed task type and cognitive strategy effects separately but not their interaction effects, which requires further exploration of appropriate analysis models in future research.

Overall, despite the small sample size, this study showed significant differences across multiple indicators, proving that different task types and cognitive strategies substantially influence user search behavior. Studying learning-oriented search from the perspective of self-regulated learning context has great potential and represents a beneficial attempt in this new field. Meanwhile, as many Internet content platforms vigorously develop knowledge-based videos as a key content innovation model, this paper's improvement suggestions for video search platforms in learning contexts, based on real experimental data, have positive implications for platform improvement and enhancing user search experience and learning efficiency.

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