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Identifying Web Information-Seeking Behavior Patterns Based on Users' Mental Models with Emphasis on Knowledge Gap Theory (A Case Study of Graduate Students Across Different Scientific Disciplines)

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ABSTRACT

The present study was conducted to identify patterns of web information-seeking behavior based on users' mental models, with an emphasis on Knowledge Gap Theory, among graduate students. The primary objective was to investigate how cognitive structures (mental models) and prior knowledge levels (academic degree) influence the effectiveness and strategies of users' web searching behavior. In terms of purpose, the study was applied research, and in terms of methodology, it employed a mixed-methods exploratory design. The statistical population consisted of graduate students from six academic fields (humanities, basic sciences, medical sciences, agriculture, engineering and technology, and arts), from which 50 participants (25 master's students and 25 doctoral students) were selected through purposive sampling. Data collection instruments included a researcher-developed Mental Model Assessment Questionnaire and observation of search behavior during two tasks of varying complexity (simple and difficult). The search process was recorded using event-capturing software (Camtasia) and subsequently coded through log-file content analysis. The findings revealed that 56% of users possessed a "moderate" mental model, 24% a "weak" mental model, and only 20% a "strong" mental model of web structures and search engines. Statistical analyses (ANOVA) indicated significant differences in search efficiency indicators; users with stronger mental models completed tasks in less time and with fewer keywords. Furthermore, comparison of the two educational groups confirmed the existence of a knowledge gap, as doctoral students, owing to their higher levels of prior knowledge, made significantly greater use of specialized databases and advanced search operators. Based on the qualitative analysis of search pathways, two distinct behavioral patterns were identified: (1) a "linear-exploratory pattern" (characteristic of users with weak mental models), marked by dependence on general search engines and frequent backtracking; and (2) a "structured-parallel pattern" (characteristic of users with strong mental models), distinguished by parallel information processing across multiple tabs and rapid source evaluation. The findings suggest that mere access to technology does not guarantee equal utilization of information resources; rather, the "mental model" functions as a cognitive filter that plays a decisive role in information-seeking behavior. Moreover, the traditional knowledge gap (based on educational attainment) is reproduced within the digital environment, placing students with lower academic levels and incomplete mental models at greater risk of information confusion. Revising information literacy education with a focus on improving users' mental models is recommended as the primary intervention strategy.

Keywords: *Information-seeking behavior, mental model, Knowledge Gap Theory, web, graduate students, log-file analysis.*

1. Introduction

The rapid expansion of digital technologies and the widespread accessibility of the World Wide Web have fundamentally transformed the ways in which individuals seek, evaluate, and utilize information. In contemporary knowledge societies, web-based information retrieval has become an indispensable component of academic, professional, and personal decision-making processes. Search engines, online databases, digital repositories, and social platforms have significantly increased access to information resources, enabling users to obtain vast quantities of information within seconds. However, the availability of information does not necessarily guarantee effective access, comprehension, or utilization. Individuals often differ substantially in their ability to formulate search strategies, evaluate sources, interpret search results, and integrate retrieved information into their knowledge structures. These differences have attracted considerable attention from researchers in information science, cognitive psychology, human-computer interaction, and knowledge management (Geczy et al., 2010; Kazempour & Nakhoda, 2016).

Web information-seeking behavior refers to the observable and cognitive activities undertaken by users when searching for information in online environments. Such behaviors include query formulation, query reformulation, source selection, navigation patterns, evaluation of retrieved information, and decision-making regarding relevance and usefulness. Previous studies have demonstrated that web searching is not merely a technical activity but rather a complex cognitive process influenced by users' prior knowledge, goals, motivations, experiences, and mental representations of information systems (Aula et al., 2010; Liu et al., 2019). Consequently, understanding the underlying cognitive mechanisms that shape information-seeking behavior has become a central concern for researchers attempting to improve information retrieval systems and information literacy programs.

One of the most influential concepts for explaining differences in user behavior is the notion of mental models. Mental models represent individuals' internal cognitive representations of how systems operate and how actions lead to outcomes. In information retrieval environments, mental models influence users' expectations regarding search engines, database structures, ranking mechanisms, hyperlinks, and information organization. When users possess accurate and sophisticated mental models, they are generally more capable of developing efficient search strategies, predicting system responses, and adapting their behavior when encountering obstacles. Conversely, incomplete or inaccurate mental models may lead to ineffective search strategies, confusion, repeated errors, and reduced retrieval performance (Lewis & Contrino, 2016; Wilkinson, 2009).

Research examining mental models in information retrieval contexts has consistently highlighted their importance in shaping user interactions with search systems. Studies have shown that students often develop simplified or inaccurate understandings of search engines, particularly regarding indexing processes, ranking algorithms, and information retrieval mechanisms. Such misconceptions may influence how users formulate queries, evaluate search results, and determine the credibility of information sources (Safari et al., 2017; Willson & Given, 2014). The increasing complexity of digital information environments further emphasizes the necessity of understanding how mental models influence search behavior and information retrieval outcomes.

The relationship between mental models and web searching has become even more significant with the emergence of advanced search technologies, personalized information systems, and artificial intelligence–driven retrieval tools. Recent investigations have demonstrated that users' understanding of search system functionality strongly affects their interactions with emerging technologies, including conversational search systems and generative artificial intelligence applications. Transparent interfaces and clearer system explanations can contribute to more accurate mental models, thereby enhancing user performance and trust in search environments (Degachi, 2025). Similarly, machine learning–based personalization systems increasingly rely on understanding user search patterns and cognitive characteristics to improve retrieval effectiveness and user satisfaction (Bedi et al., 2022; Subbarayudu & Reddy, 2025).

Another theoretical framework that provides valuable insight into information-seeking behavior is Knowledge Gap Theory. Originally developed to explain inequalities in information acquisition across social groups, the theory proposes that individuals with higher socioeconomic status, educational attainment, and prior knowledge tend to acquire new information more rapidly than those with fewer resources. As information availability increases, knowledge disparities often widen rather than diminish because individuals differ in their capacity to access, interpret, and utilize information effectively (Keikha & Moradi Siasar, 2015). Although the theory was initially developed in the context of mass communication, its relevance has expanded considerably in digital environments where information abundance coexists with substantial differences in information literacy and search competence.

The application of Knowledge Gap Theory to web searching suggests that access to technology alone is insufficient for ensuring equitable information acquisition. Individuals possessing stronger cognitive foundations, higher educational levels, and more sophisticated information-seeking skills are often better equipped to exploit digital resources effectively. In contrast, users with limited prior knowledge may experience information overload, difficulty evaluating sources, and inefficient search behaviors. Consequently, digital technologies may reproduce or even amplify existing knowledge inequalities despite providing universal access to information resources (Khodabakhsh et al., 2024; Mohammadpour et al., 2023).

Several empirical investigations have examined factors influencing web information-seeking behavior among students and academic users. Research has shown that cognitive abilities, information literacy competencies, and prior academic experience significantly affect search effectiveness and retrieval outcomes. Users with stronger cognitive skills tend to formulate more precise queries, navigate information environments more efficiently, and evaluate source credibility more accurately than users with weaker cognitive capabilities (Khodabakhsh et al., 2024). Similarly, doctoral students often demonstrate more advanced information retrieval skills than master's students because of their greater research experience, disciplinary knowledge, and familiarity with scholarly databases (Mohammadpour et al., 2023).

Task characteristics also play an important role in shaping search behavior. Search tasks vary considerably in terms of complexity, determinability, ambiguity, and cognitive demands. Difficult or ill-structured tasks often require extensive exploration, query reformulation, and source evaluation, whereas simple tasks may be completed through straightforward retrieval strategies. Studies have demonstrated that increasing task complexity substantially affects user behavior, leading to longer search sessions, more query modifications, and greater navigation depth (Aula et al., 2010; Kelly et al., 2015). Similarly, task determinability has been shown to influence search strategies and retrieval outcomes, with users exhibiting different behavioral patterns depending on their ability to identify clear solution paths (Capra et al., 2018).

Query formulation and reformulation constitute another critical dimension of information-seeking behavior. Effective search performance often depends on users' ability to translate information needs into appropriate search expressions. Research examining query reformulation behavior has revealed that successful users frequently modify their search terms based on feedback from retrieved results, whereas less successful users tend to persist with ineffective queries or engage in random reformulations (Chen et al., 2021). Such findings underscore the importance of cognitive flexibility and system understanding in successful information retrieval.

The increasing availability of web tracking technologies and behavioral analytics has enabled researchers to investigate search behavior with unprecedented precision. Studies employing clickstream analysis, log-file analysis, and behavioral tracking have revealed substantial variability in search patterns across users, contexts, and tasks. Comparative analyses indicate that users differ not only in what they search for but also in how they navigate information environments, evaluate results, and allocate attention during search sessions (Urman & Makhortykh, 2023). These findings highlight the necessity of examining search behavior as a multidimensional phenomenon influenced by both cognitive and contextual factors.

Recent studies conducted in academic environments have further emphasized the importance of understanding information-seeking behavior among university students and researchers. Investigations involving postgraduate students have reported considerable differences in search strategies, relevance judgments, and information evaluation practices. While some users employ systematic and analytical approaches, others rely heavily on superficial cues such as ranking position or source familiarity when selecting information resources (Momen et al., 2023). Multilingual information retrieval studies have similarly demonstrated that language proficiency influences access to information and retrieval effectiveness, particularly in contexts where scholarly resources are predominantly available in English (Moazzami et al., 2023).

The significance of web search behavior extends beyond academic contexts and has been examined in various social, health, and professional domains. Analyses of web search data have been used to investigate public interest in health-related issues, disease outbreaks, and social phenomena. For example, web search behavior has been employed to monitor public responses to sexually transmitted infections and public health crises such as COVID-19, demonstrating the broader societal relevance of online information-seeking activities (Pilz et al., 2021; Rovetta & Bhagavathula, 2020). These studies illustrate how web search behavior reflects underlying cognitive, informational, and social processes.

From a decision-making perspective, effective information seeking is essential for reducing uncertainty and improving judgment quality. Research indicates that web use can significantly influence decision outcomes, particularly in situations characterized by ambiguity and incomplete information. Users who are capable of efficiently locating and evaluating relevant information are generally more successful in addressing ill-structured problems than those who struggle with information retrieval processes (McLain & Wu, 2022). This observation reinforces the importance of understanding the cognitive mechanisms underlying search behavior.

Despite substantial advances in information retrieval research, several gaps remain. First, many studies focus primarily on observable search behaviors while paying limited attention to the underlying mental models that generate such behaviors. Second, relatively few investigations have integrated cognitive perspectives with Knowledge Gap Theory to explain differences in search performance among users with varying educational backgrounds. Third, most existing studies examine either mental models or search behavior independently rather than exploring their interactive relationship within real-world academic environments (Safari et al., 2017; Wilkinson, 2009). Furthermore, recent investigations conducted among researchers and postgraduate students suggest that significant variations in search competence continue to exist despite increasing digital literacy initiatives (Feyzollahi et al., 2020; Mirhosseini et al., 2025).

Graduate students constitute an especially important population for investigating these issues because they engage extensively with digital information resources for research, learning, and scholarly communication. Their academic success depends heavily on their ability to locate, evaluate, and utilize high-quality information. At the same time, graduate students represent diverse disciplinary backgrounds and educational experiences, providing an appropriate context for examining how mental models and knowledge gaps influence information-seeking behavior. Understanding these relationships may contribute to the development of more effective information literacy programs, improved search system designs, and targeted interventions for reducing disparities in information access and retrieval performance (Mirhosseini et al., 2025; Mthembu, 2019).

Given the theoretical significance of mental models, the explanatory power of Knowledge Gap Theory, and the practical importance of effective information retrieval in academic environments, this study aims to identify patterns of web information-seeking behavior based on users' mental models, with particular emphasis on Knowledge Gap Theory, among graduate students from different scientific disciplines.

2. Methods and Materials

This study is quantitative in terms of the type of data collected and analyzed, and the library research method was used to collect information on the literature and research background. Accordingly, the required information was collected through reviewing books, articles, and studies conducted by other researchers. The present study is also applied in terms of objective, because its findings can be used to solve specific problems. The statistical population of the study consisted of doctoral and master's students in six scientific fields (humanities, basic sciences, medical sciences, agricultural sciences, engineering and technology, and arts) who regularly use the World Wide Web to meet their information needs in their academic and personal activities. The population included 400 individuals, and the sample consisted of 50 doctoral and master's students who were selected as participants through convenience sampling and were assigned through random allocation to a 25-person group (experimental group).

In the present study, purposive sampling was used. The most important data collection methods in this study were as follows:

Documentary and library studies: At the beginning of the study, in order to strengthen the theoretical foundations of the research and use the results of previous studies related to the research topic, a comprehensive review of documents, records, and library sources, including books, student theses, project reports, journals, and scientific-research journals, was conducted. These studies included books or articles, documents, academic theses, and sources related to the topic, as well as the Internet, for collecting and reviewing information.

Field study: After reviewing documents and collecting information through library sources, the grounded theory method and in-depth interviews with experts were used. In this section, face-to-face interviews were conducted with experts and specialists to obtain the required information. This information was particularly effective in validating, revising, and developing the questionnaire.

The data analysis method in the study titled "Identifying Web Information-Seeking Behavior Patterns Based on Users' Mental Models with Emphasis on Knowledge Gap Theory" was designed quantitatively and quasi-experimentally, and included the analysis of data collected from mental model questionnaires, search tasks, and data recorded by Camtasia software.

First, the data obtained from the mental model questionnaires were analyzed to identify the mental models of master's and doctoral students in six scientific fields (humanities, basic sciences, medical sciences, agricultural sciences, engineering and technology, and arts). The questionnaire responses were entered into software such as SPSS or Excel and were cleaned for errors, incomplete responses, or outliers. Then, descriptive statistical indices such as mean, standard deviation, and median were calculated for each item or scale. The distribution of the data was examined using tests such as the Kolmogorov–Smirnov test in order to determine appropriate analytical methods. If the questionnaire included multiple scales, exploratory or confirmatory factor analysis was used in software such as SPSS to extract the dimensions of mental models, and these models were classified into categories such as linear, nonlinear, or experience-based models. To compare mental models across scientific fields or educational levels, statistical tests such as ANOVA or the independent-samples t-test were used. The extracted mental models were compared with the framework of Knowledge Gap Theory to determine the effect of knowledge gaps on the structure of mental models. The output of this stage included the classification of dominant mental models, the identification of significant differences between groups, and statistical reports accompanied by descriptive charts such as box plots or histograms. In the next stage, the data recorded by Camtasia software were analyzed to identify behavioral patterns of information searching in simple and complex tasks. First, the Camtasia video files were reviewed, and variables such as the number and type of keywords used, navigation path, time spent at each stage, and the type and credibility of selected sources were extracted. Descriptive indices such as the mean number of keywords, search time, or number of reviewed sources were calculated for each task and scientific field, and descriptive charts such as bar charts were drawn. Cluster analysis was used to identify similar patterns in search behavior, and sequence analysis was employed to examine the order of users' actions, such as the sequence of keywords or clicks. Differences in search behavior between simple and complex tasks were examined using the paired-samples t-test, and differences across scientific fields or educational levels were analyzed using ANOVA or nonparametric tests. Search behaviors were compared with the mental models extracted from the questionnaires, and correlation analysis, such as Pearson correlation, was used to examine the relationship between mental model variables and search behavior. The output of this stage included search behavior patterns, flowcharts or heat maps for displaying search paths, and reports of significant differences between groups and tasks. Finally, questionnaire and Camtasia data were integrated into a common database to map the relationship among mental models, search patterns, and the knowledge gap. Key variables such as type of mental model, number of keywords, and search time were prepared for integrated analyses. Correlation analysis was used to examine the relationship between mental models and search patterns, and multiple regression analysis was used to predict search behavior based on mental models and demographic variables. Search patterns were visualized using tools such as Tableau or Power BI in the form of flowcharts or graphical models, and theoretical models based on Knowledge Gap Theory were presented to explain behavioral differences. The reliability of the questionnaire data was confirmed using Cronbach's alpha coefficient, and the validity of the Camtasia data was confirmed through multiple reviews by researchers. The findings were compared with Knowledge Gap Theory, and solutions for reducing the knowledge gap, such as search skills training, were proposed. The final output included a comprehensive model of the relationship between mental models and search patterns, statistical reports, visualization charts, and scientific and practical recommendations.

3. Findings and Results

The individual and contextual characteristics of the participants, including gender, educational level, field of study, and information-searching habits, are presented. Examining these characteristics provides a clear picture of the study population. A summary of the descriptive statistics is shown in Table 1.

Table 1

Frequency Distribution of Demographic Characteristics

Variable	Levels / Categories	Frequency (n)	Frequency Percentage
Gender	Female	27	54%
	Male	23	46%
Educational level	Master's degree	25	50%
	Doctoral degree	25	50%
Field or academic discipline	Humanities	7	14%
	Basic sciences	6	12%
	Medical sciences	5	10%
	Agricultural sciences	9	18%
	Engineering and technology	4	8%
	Arts	19	38%
Internet use experience	Less than 3 years of Internet experience	2	4%
	3 to 5 years	10	20%
	6 to 10 years	21	42%
	More than 10 years	17	34%
Weekly use of the Internet for searching scientific information	1 to 3 hours of weekly use	20	40%
	4 to 7 hours	22	44%
	More than 7 hours	8	16%
Most important source for searching scientific information	Search engines	15	30%
	Scientific databases	24	48%
	Social networks	3	6%
	Specialized websites	4	8%
	Other	4	8%
Level of mastery of web information-searching skills	Very low mastery	1	2%
	Low	3	6%
	Moderate	18	36%
	High	25	50%
	Very high	3	6%
Not specified in the source text	Yes	23	46%
	No	27	54%
Languages used for information searching	Persian	10	20%
	English	7	14%
	Both	31	62%
	Other	1	2%
Average time spent finding required information in each search session	Less than 15 minutes per session	10	20%
	15 to 30 minutes	22	44%
	30 to 60 minutes	15	30%
	More than 1 hour	3	6%
Main tool used for searching	Personal computer	4	8%
	Laptop	25	50%

	Mobile phone	16	32%
	Tablet	5	10%
Experience in research or scientific article writing	Yes	50	100%

As shown in Table 1, the gender composition of the sample was almost balanced (54% female and 46% male). An important point in this study is the completely equal distribution of participants across the two educational levels of master's degree (50%) and doctoral degree (50%), which makes it possible to accurately compare the effect of educational level on search behavior based on Knowledge Gap Theory.

Table 2

Detailed Descriptive Statistics of Items Measuring Users' Mental Models

No.	Questionnaire Item	Mean	Standard Deviation	Status
1	I consider the structure of the web to be like a large classified library (metaphorical model).	3.8	0.92	Favorable
2	I know exactly on what basis search engines rank results (technical model).	2.1	0.85	Weak
3	Before starting a search, I can mentally map the path to reaching the answer (planning).	3.1	1.05	Moderate
4	I know the difference between searching the "Deep Web" and the public web.	1.95	0.78	Weak
5	When I search, I have an accurate understanding of how Google finds pages (crawling).	2.45	1.1	Weak
6	I can guess why some links appear on the first page and others on later pages.	2.8	0.95	Moderate
7	When a search fails, I change my strategy based on the logic of the search engine.	3.5	1.12	Moderate
8	I use Boolean operators (AND, OR) and advanced operators to make my search more precise.	2.4	1.25	Weak
—	Overall mean score of mental model	2.76	0.88	Moderate

Based on the developed methodology, the scores were classified into the following three levels:

Weak mental model (incomplete): score of 8 to 18

Moderate mental model: score of 19 to 29

Strong mental model (complete): score of 30 to 40

Table 3

Frequency and Percentage Distribution of Users' Mental Model Levels

Mental Model Level	Score Range	Frequency (n)	Frequency Percentage	Group Mean Score	Standard Deviation
Weak mental model (incomplete)	8 to 18	12	24%	16.5	1.25
Moderate mental model	19 to 29	28	56%	24.3	2.1
Strong mental model (complete)	30 to 40	10	20%	32.8	1.85
Total / Overall mean	8 to 40	50	100%	24.12	4.32

As shown in Table 3, the overall mean mental model score of the respondents was 24.12 out of a total score of 40, indicating that users' overall understanding of the structure of the web and search mechanisms was at a "moderate" level.

The findings indicate that merely having higher education, even at the doctoral level, does not guarantee a complete and technical mental model of how search engines operate. According to Norman's theory, this weakness in the mental model can lead to errors in predicting search results and reduce efficiency in information retrieval, which will be tested in the following sections through the analysis of search behavior.

The data extracted from frame-by-frame analysis of the videos recorded in Camtasia software are summarized in Table 4.

Table 4. Descriptive Statistics of Search Behavior

Table 4

Indicators by Task Type

Behavioral Variable	Task Type	Mean	Median	Standard Deviation	Range (Min–Max)
Search time (seconds)	Simple	223.7	210	45.3	100 to 450
	Difficult	413.8	390	82.1	180 to 920

Number of keywords (queries)	Simple	2.8	2	1.2	1 to 6
	Difficult	4.4	4	2.1	1 to 12
Number of visited pages	Simple	5.6	5	2.5	2 to 15
	Difficult	9.7	8	4.3	3 to 25

In Table 5, the means of these indicators are presented separately for the three mental model groups (weak, moderate, and strong) in order to reveal behavioral differences resulting from the level of the mental model.

Table 5

Comparison of the Mean Quantitative Indicators of Search Behavior Across Different Mental Model Groups

Search Behavior Indicator	Task Type	Weak Mental Model (n = 12)	Moderate Mental Model (n = 28)	Strong Mental Model (n = 10)	Total (n = 50)	F Value (Significance)*
Search duration (seconds)	Simple	345.5	210.4	115.2	223.7	8.45 (0.001)**
	Difficult	580.2	420.6	240.8	413.8	12.30 (0.000)**
Number of keywords (queries)	Simple	4.2	2.8	1.5	2.8	5.12 (0.014)*
	Difficult	6.8	4.1	2.3	4.4	6.88 (0.005)**
Number of visited nodes (clicks/nodes)	Simple	8.5	5.2	3.1	5.6	4.32 (0.021)*
	Difficult	14.3	9.6	5.4	9.7	7.15 (0.003)**

** Significant difference at the 0.01 level

The findings indicate an inverse and significant relationship between the level of mental model and the time spent on searching. Users with a strong mental model completed the simple task in an average of 115 seconds (less than 2 minutes), whereas the group with a weak mental model spent 345 seconds (more than 5 minutes) on the same task. This difference became much more pronounced in the difficult task; the weak group spent more than 9 minutes (580 seconds), indicating confusion in formulating a search strategy. One of the most accurate methods for extracting patterns is the use of a "state transition matrix." This matrix shows the probability, expressed as a percentage, that when a user with a specific mental model is in one state, such as the Google results page, they will move to the next state. In Table 6, the behavioral transition matrix was calculated for the two groups with weak and strong mental models.

Table 6

Behavioral Transition Probability Matrix in Two User Groups

Current State (Origin)	Next State (Destination)	Transition Probability in the Weak Mental Model Group	Transition Probability in the Strong Mental Model Group	Interpretation of Difference
Start of search	Selecting a general search engine (Google)	100%	20%	Absolute dependence of the weak group on Google
	Selecting a scientific database (direct URL)	0%	80%	Professional behavior in the strong group
Results page (SERP)	Clicking on the first result (first link)	85%	30%	Hasty behavior in the weak group
	Scanning and reviewing titles	15%	70%	Careful evaluation in the strong group
Viewing content	Returning to the results page (Back button)	60%	10%	Pogo-sticking phenomenon (confusion)
	Extracting/saving information	20%	85%	High success in the strong group
	Closing the page without result	20%	5%	Retrieval failure

In the weak mental model group, the probability of transition from "viewing content" to the "results page" was 60%. This means that the user enters a website, finds it irrelevant, and clicks the Back button. Repetition of this cycle leads to wasted time and user fatigue (linear pattern). In the strong group, the probability of transition from "viewing content" to "saving information" was 85%. This means that, before clicking, the user ensures the usefulness of the source by reading the abstract or summary during the scanning stage and reaches the goal with minimal error (direct pattern). Tichenor's Knowledge Gap Theory states that individuals with a higher academic base process information at a different quality level. To demonstrate this issue in the web environment, the vocabulary used by master's and doctoral students in the difficult task was analyzed in terms of "specialization" and "language." The results are compared in Table 7.

Table 7

Qualitative Comparison of Word-Selection Strategies Between Master's and Doctoral Students (Knowledge Gap Test)

Lexical Indicator	Master's Students (n = 25)	Doctoral Students (n = 25)	Knowledge Gap Analysis
Dominant type of vocabulary	General and descriptive words (e.g., "article about...," "what is?")	Specialized and technical terms (thesaurus terms)	Doctoral students have greater mastery of the "indexing language."
Search language	Persian (60%) / English (40%)	English (90%) / Persian (10%)	Language proficiency is a key factor in creating the access gap.
Length of search phrase	Long and sentence-like phrases (natural language) (mean: 5.2 words)	Short and combined keywords (mean: 3.4 words)	Doctoral students use "Boolean Logic."
Use of operators	Very limited (only 2 individuals)	Extensive (18 individuals) (use of " ", filetype, site:)	Higher technical skill is evident in the doctoral group.

Table 7 shows that the knowledge gap on the web is rooted in a "lexical gap." Master's students, as the lower-level group, attempt to communicate with Google in natural language and Persian, whereas high-quality scientific content is often indexed in English and with technical terms. In contrast, doctoral students, by using specialized vocabulary (thesaurus terms) and operators, employ precisely the same language for which information retrieval systems are designed. This difference in "input" leads to a substantial difference in "output" and access to information.

Based on the integration of data from the transition matrix (Table 6) and lexical analysis (Table 7), two comprehensive behavioral patterns were extracted and illustrated (Figure 1) and (Figure 2).

Figure 1

Linear and Exploratory Search Pattern (Specific to Users with Weak Mental Models and a High Knowledge Gap)

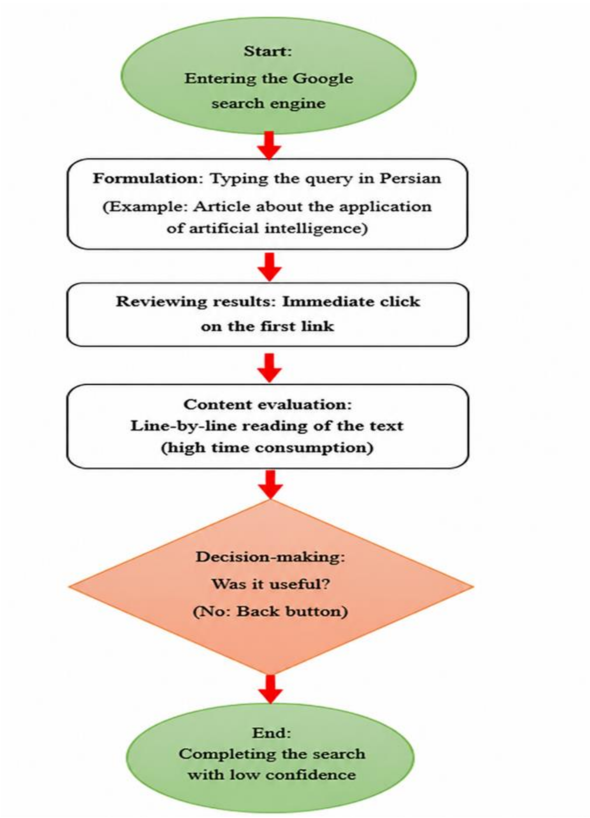
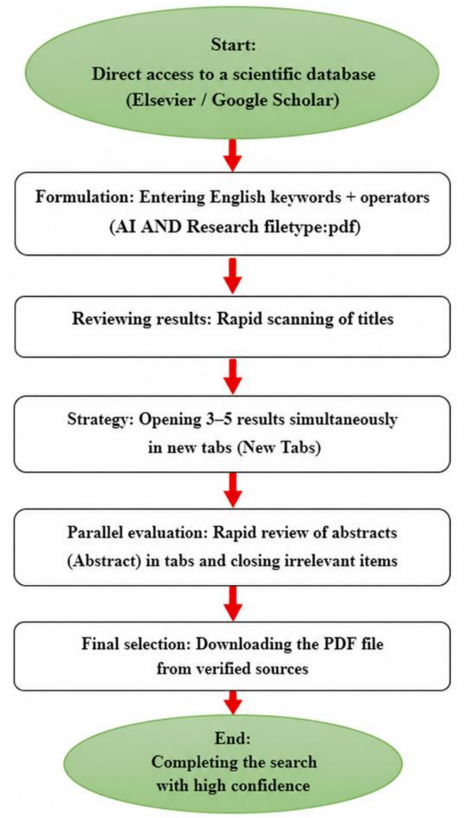


Figure 2

Structured and Parallel Search Pattern (Specific to Users with Strong Mental Models and a Low Knowledge Gap)



This pattern is characterized by a direct path, parallel processing in browser tabs, and the use of operators. In this section, the search behavior of 50 graduate students was analyzed using a mixed method, including questionnaire and behavioral observation. The descriptive findings showed that 56% of users had a moderate mental model and 24% had a weak mental model. Statistical analyses (ANOVA and t-test) demonstrated that there was a significant relationship between "level of mental model" and "search efficiency indicators"; users with strong mental models achieved more accurate results in less time and with fewer keywords. Moreover, comparison of the master's and doctoral groups confirmed the existence of a "knowledge gap"; doctoral students used more specialized search strategies because of their higher prior knowledge. Finally, two behavioral patterns, namely the "linear-exploratory" pattern and the "structured-parallel" pattern, were extracted, indicating the direct effect of cognitive structures on users' interaction with the web environment.

4. Discussion and Conclusion

The present study aimed to identify patterns of web information-seeking behavior based on users' mental models with an emphasis on Knowledge Gap Theory among graduate students from different scientific disciplines. The findings revealed several important patterns regarding the cognitive foundations of web searching, the role of educational background in information retrieval, and the emergence of distinct search behavior patterns among users. Overall, the results demonstrated that users' mental models significantly influenced their search efficiency, search strategies, navigation behavior, and success in retrieving relevant information. Furthermore, the findings confirmed that differences in prior knowledge and educational attainment contribute to the persistence of knowledge gaps within digital environments.

One of the most important findings of the study was that the majority of participants possessed only a moderate mental model of the web and search engines, while a considerable proportion demonstrated weak mental models and only a small percentage exhibited strong and technically sophisticated mental models. This finding suggests that even among graduate students, who are expected to have substantial experience with digital information resources, a comprehensive understanding of how search systems operate remains limited. This result is consistent with previous studies that reported incomplete or inaccurate mental representations of search engines among university students and academic users (Safari et al., 2017; Wilkinson, 2009). Similar findings were reported by Lewis and Contrino, who argued that users frequently construct simplified cognitive representations of information systems that do not accurately reflect the underlying mechanisms of retrieval technologies (Lewis & Contrino, 2016). The present findings therefore reinforce the argument that frequent use of web technologies does not necessarily lead to a deeper understanding of their operational logic.

The analysis of specific mental model components revealed that participants demonstrated relatively stronger metaphorical understandings of the web but weaker technical understandings of search engine ranking, web crawling, deep web structures, and advanced search functionalities. This pattern is theoretically meaningful because users tend to construct mental models based on visible interactions rather than invisible computational processes. According to mental model theory, individuals develop cognitive representations through direct experience and observable feedback; therefore, aspects of search systems that remain hidden from users are often poorly understood (Degachi, 2025; Willson & Given, 2014). The findings suggest that many users rely on intuitive assumptions regarding search engine functionality rather than evidence-based understanding, which may negatively affect their ability to formulate efficient search strategies.

Another significant finding was the strong relationship between mental model quality and search efficiency indicators. Users with stronger mental models completed search tasks significantly faster, used fewer search terms, and visited fewer pages than users with weaker mental models. These findings indicate that accurate cognitive representations allow users to formulate more effective search strategies and make better decisions during the search process. This result aligns closely with previous research demonstrating that cognitive factors play a central role in information retrieval performance. Khodabakhsh et al. reported that individuals with stronger cognitive abilities exhibit superior search performance and greater efficiency in navigating web environments (Khodabakhsh et al., 2024). Likewise, studies examining information-seeking intentions and user behavior have shown that successful searchers are generally more strategic and goal-oriented in their interactions with search systems (Liu et al., 2019).

The observed relationship between mental models and search efficiency can also be interpreted from a cognitive load perspective. Users with strong mental models possess clearer expectations regarding system behavior and therefore expend fewer cognitive resources on trial-and-error activities. In contrast, users with weak mental models frequently engage in exploratory behaviors that increase cognitive burden and prolong task completion times. Similar conclusions were reported by Aula et al., who found that search difficulty leads to substantial changes in user behavior, particularly among users who lack effective cognitive frameworks for navigating information environments (Aula et al., 2010). The present findings further support the proposition that mental models function as cognitive maps that reduce uncertainty and facilitate efficient decision-making during information retrieval.

The results also demonstrated that task complexity significantly influenced search behavior. Participants spent considerably more time, used more keywords, and visited more pages when completing difficult tasks compared to simple tasks. This finding is consistent with established information retrieval literature indicating that complex and ill-defined tasks require more extensive exploration, information evaluation, and query reformulation (Capra et al., 2018; Kelly et al., 2015). As task complexity increases, users must process larger volumes of information and engage in more sophisticated cognitive activities. The present study extends these findings by demonstrating that the influence of task complexity is moderated by mental model quality. Users with strong mental models were able to manage complexity more effectively, whereas users with weak mental models experienced substantial increases in search time and navigation complexity.

The transition matrix analysis provided particularly valuable insights into the cognitive mechanisms underlying search behavior. The findings showed that users with weak mental models exhibited a high probability of immediately selecting general search engines, clicking on top-ranked results, and repeatedly returning to search result pages. This pattern reflects what may be described as a trial-and-error or reactive search strategy. In contrast, users with strong mental models were more likely to access specialized databases directly, carefully scan search results, and successfully extract information after evaluating source relevance. These findings are highly consistent with research demonstrating that experienced searchers engage in more systematic evaluation processes and rely less on superficial cues such as ranking position (Geczy et al., 2010; Momen et al., 2023).

The phenomenon of repeated returns to search result pages observed among users with weak mental models is particularly noteworthy. This behavior resembles the pogo-sticking phenomenon frequently discussed in information retrieval research, where users repeatedly move between search results and content pages because retrieved information fails to satisfy their information needs. Such behavior often reflects poor query formulation, inaccurate relevance judgments, or insufficient understanding of search system functionality. The current findings suggest that weak mental models contribute directly to these inefficiencies by limiting users' ability to anticipate the usefulness of information sources before accessing them (Chen et al., 2021).

A major contribution of the study lies in its examination of Knowledge Gap Theory within contemporary digital environments. The comparison between master's and doctoral students revealed clear differences in search strategies, vocabulary usage, language selection, and utilization of advanced search operators. Doctoral students demonstrated greater use of technical terminology, English-language searches, specialized databases, and advanced search functions, whereas master's students relied more heavily on natural language queries and general search engines. These findings provide strong empirical support for Knowledge Gap Theory by demonstrating that individuals with higher levels of prior knowledge and educational attainment acquire and process information more effectively than those with lower levels of knowledge (Keikha & Moradi Siasar, 2015).

The linguistic dimension of the knowledge gap is especially significant. The findings indicated that doctoral students conducted the majority of their searches in English, whereas master's students relied more heavily on Persian-language searching. Because a substantial proportion of high-quality scientific information is indexed and disseminated in English, language proficiency becomes an important mechanism through which knowledge inequalities are reproduced. Similar conclusions were reached by Moazzami et al., who found that multilingual users experience significant differences in information retrieval effectiveness depending on their language competencies (Moazzami et al., 2023). Thus, the knowledge gap in digital environments may not only reflect differences in educational attainment but also differences in linguistic and technical competencies.

The extensive use of advanced search operators among doctoral students further illustrates how prior knowledge influences information retrieval outcomes. Advanced operators allow users to communicate with search systems using more precise and structured expressions, thereby improving retrieval effectiveness. This finding is consistent with studies showing that expert users possess greater awareness of search system functionalities and are more capable of adapting their strategies to different search contexts (Bedi et al., 2022; Mohammadpour et al., 2023). Consequently, knowledge gaps manifest not only in the amount of information acquired but also in the quality and efficiency of information retrieval processes.

The identification of two distinct behavioral patterns—the linear-exploratory pattern and the structured-parallel pattern—represents another important contribution of the study. The linear-exploratory pattern was characterized by repetitive navigation, natural language searching, reliance on general search engines, and frequent backtracking. This pattern was predominantly associated with users who possessed weak mental models and higher levels of knowledge gap. In contrast, the structured-parallel pattern involved direct access to specialized resources, simultaneous evaluation of multiple sources, efficient query formulation, and rapid decision-making. This pattern was characteristic of users with strong mental models and lower levels of knowledge gap.

These behavioral patterns support recent evidence suggesting that users can be classified according to stable information-seeking styles and behavioral tendencies (Subbarayudu & Reddy, 2025). Similar distinctions have been observed in studies employing web tracking and behavioral analytics approaches, which found substantial differences in navigation strategies and information evaluation practices across user groups (Urman & Makhortykh, 2023). The present findings contribute to this literature by demonstrating that such behavioral differences are closely linked to underlying cognitive structures and educational experiences.

The findings also have implications for understanding information behavior in an era increasingly influenced by artificial intelligence and intelligent retrieval systems. As search technologies become more sophisticated, users who possess strong mental models may be better positioned to exploit new functionalities, whereas those with weak mental models may struggle to benefit from technological advances. Recent studies examining conversational search systems emphasize the importance of transparency and user understanding in facilitating effective interactions with intelligent retrieval technologies (Degachi, 2025). Therefore, addressing deficiencies in users' mental models may become increasingly important as search environments continue to evolve.

Overall, the findings suggest that cognitive structures, prior knowledge, and educational experiences remain critical determinants of information retrieval success despite widespread access to digital technologies. The persistence of significant differences among users indicates that technological access alone is insufficient for achieving information equality. Rather, effective information acquisition depends upon the interaction of cognitive, educational, linguistic, and technological factors. The study therefore supports both Mental Model Theory and Knowledge Gap Theory as complementary frameworks for explaining variations in web information-seeking behavior.

This study has several limitations that should be considered when interpreting the findings. First, the sample size was relatively limited and consisted exclusively of graduate students, which may restrict the generalizability of the findings to other populations such as undergraduate students, faculty members, or the general public. Second, the study focused on six disciplinary areas and may not fully capture disciplinary variations present across broader academic contexts. Third, search behavior was examined using predefined tasks that may not perfectly reflect real-world information needs and natural searching situations. Finally, although behavioral observation and questionnaire data provided valuable insights, additional qualitative methods such as think-aloud protocols could have generated deeper understanding of users' cognitive processes during searching.

Future studies should investigate larger and more diverse populations in order to examine the generalizability of the identified behavioral patterns. Longitudinal research designs could be employed to examine how mental models develop over time and how information literacy interventions influence search behavior. Researchers may also explore the role of emerging technologies such as generative artificial intelligence, conversational search systems, and recommendation algorithms in shaping users' mental models and information-seeking strategies. Comparative cross-cultural studies could further examine how linguistic, educational, and technological factors interact to influence knowledge gaps in digital environments. Additionally, mixed-method studies incorporating interviews, eye-tracking, and think-aloud protocols may provide richer insights into the cognitive mechanisms underlying search behavior.

The findings highlight the importance of redesigning information literacy programs to focus not only on search techniques but also on improving users' conceptual understanding of how search systems operate. Universities should provide training that explicitly addresses search engine functionality, database structures, query formulation strategies, and source evaluation skills. Academic libraries can develop targeted workshops for students with weaker search competencies and create learning resources that promote more sophisticated mental models of information retrieval systems. Search system designers should consider developing interfaces that enhance transparency and provide users with clearer explanations regarding search processes and ranking mechanisms. Finally, educational institutions should encourage the development of English-language information retrieval skills and advanced search competencies to reduce knowledge disparities and improve access to high-quality scientific information.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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