Extraction and Evaluation of User Paths in Mobile Search Systems (Postprint)

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Abstract

[Purpose/Significance] To extract users' complete paths of mobile web search system usage and switching, and to reveal differences among different web search system usage paths in terms of process, outcomes, and other dimensions. [Method/Process] Employing an experimental research methodology combined with questionnaires and interviews, and from the perspective of mobile search system usage, we designed complex search tasks across two distinct themes, extracted users' search system usage paths with search systems as nodes, applied cluster analysis methods to discover and summarize multiple specific patterns of mobile users' search system usage paths, and evaluated and analyzed each pattern from three aspects: search process, search results, and exploratory search performance. [Results/Conclusion] Mobile users exhibit varying preferences for search systems under different task themes; users' search system usage paths exhibit specific patterns; and users' evaluations of search paths differ across these patterns.

Full Text

Preamble

Extracting and Evaluating User Search Trails on Mobile Search Systems

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Abstract:
[Purpose/Significance] This study extracts users' complete trails of search system usage and switching on mobile devices, revealing differences in process and outcomes among various mobile search system usage trails. [Method/Process] Using experimental research methods combined with questionnaires and interviews, this paper designs complex search tasks under two different topics from the perspective of mobile search system usage. Search systems are treated as nodes to extract users' search trails, and cluster analysis is employed to discover and summarize specific patterns of mobile user search trails. Each pattern is evaluated and analyzed from three aspects: search process, search results, and exploratory search performance. [Result/Conclusion] Mobile users exhibit different preferences for search systems under different task topics. Specific patterns exist in users' search system usage trails, and users' evaluations of these trails differ across patterns.

Keywords: mobile search, search system, search behavior, search trail, search trails on search systems
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For factual information needs with clear objectives, such as real-time weather, birthdays, or historical events, users can typically obtain answers from a single search system. However, for complex information needs characterized by ambiguous goals, uncertain answers, and strong subjective elements—such as students completing research reports, travelers planning comprehensive itineraries, or product managers conducting competitive analysis—users often need to formulate a series of queries and employ continuous search behaviors across multiple information search systems, resulting in cross-system information search.

Existing research has extensively examined comparisons of web search systems [1], user preferences for different online information sources [2], differences in user information behavior across search systems [3], and search engine switching [4]. However, these studies fail to provide a complete picture of search system usage and switching during users' search processes, nor do they reveal differences in process and outcomes among various web search system usage trails. This research gap is particularly pronounced in the mobile internet environment, where the diversity and convenience of mobile search systems enable more frequent system switching and cross-system search behaviors. Current research pays insufficient attention to cross-system search behavior characteristics in mobile environments, limiting understanding of users' search system usage behaviors and hindering the development of mobile search systems oriented toward the entire search process.

Meanwhile, the convenience and timeliness of smartphones and other mobile terminals have made mobile search the norm. On mobile devices, users primarily employ search engines and various apps (including vertical applications and social applications). Different systems contain information with distinct characteristics: mobile search engines return highly structured information, social apps display real-time social information, and Q&A platform apps offer more personalized content. The richness of mobile search systems and the ease of switching between them allow users to select systems based on their information needs, making cross-system and cross-app search behaviors more common.

This study takes search system usage trails as its entry point, connecting multiple search systems used by users during mobile search processes into trails, and compares different trail types from multiple dimensions including process evaluation, result evaluation, and exploratory search performance evaluation. The aim is to enrich the theoretical system of mobile search behavior research and provide references for the design and development of mobile search systems. In this paper, search system usage trails are defined as: the sequence formed by connecting different search systems used by users during the completion of a complete search task.

2 Related Research

2.1 Mobile Search

Mobile search has become users' primary search method, with research on mobile search user behavior emerging as a key focus. Researchers have conducted extensive studies on search motivations and behaviors, with some focusing on user behavior within specific search systems.

In mobile internet environments, users' search motivations are closely related to their contextual states, including geographic location, time, and environment. D. Wu et al. [5] summarized six categories of mobile search motivations: curiosity, time-killing, knowledge-seeking, life services, social relations, and others, finding that approximately 25% of mobile searches are triggered by multiple motivations and that search motivations influence user search behavior. Yang Haifeng [6] constructed a mobile user search behavior model from three aspects: user information needs, information search process, and evaluation/processing of search results. The study found that on mobile devices, user information needs, triggers, and types differ from traditional desktop search, inseparable from the unique context and devices of mobile environments.

Regarding search behavior, researchers have conducted a series of empirical studies using controlled or uncontrolled methods based on actual mobile search usage data, analyzing mobile search behavior characteristics and proposing development suggestions for mobile search systems. J. Yi et al. [7] analyzed 20 million English queries submitted by users in the US, Canada, Europe, and Asia through mobile devices to the Yahoo! oneSearch application, examining query distribution and topics to extract mobile search patterns and characteristics. K. Church et al. [8] analyzed approximately 6 million individual search requests to understand European mobile searchers' patterns and mobile search engine feedback performance through key features such as click-through rates. Wu Dan et al. [9] recorded mobile transaction logs of college students through uncontrolled experiments, discovering that college students' mobile search behavior exhibits search system interaction characteristics, with a greater tendency to use vertical apps rather than traditional search engines and browsers. J. Kim et al. [10] conducted eye-tracking experiments across three mobile screen sizes (early smartphones, latest smartphones, and phablets), finding no significant differences in search efficiency across screen sizes but different search behaviors including eye movement and finger interaction patterns. J. Kim et al. [11] and P. Wang et al. [12] studied and evaluated mobile information search performance based on user interaction behaviors with search results, such as vertical scrolling and horizontal pagination, proposing suggestions for mobile search engine page design, content presentation, and interaction design.

Mobile search has been widely applied in mobile browsers, search engines, and general functional searches, with various mobile applications incorporating search functions, forming numerous mobile search systems that comprehensively serve people's life, work, and entertainment needs. B. Stvilia et al. [13] found in studying college students' health information search behavior on mobile devices that websites were the most frequently used health information source, followed by mobile applications, family, and friends. Wu Dan et al. [14] analyzed user retrieval behavior differences between WAP and APP access methods through log data analysis of a university library OPAC system. Sun Jie et al. [15] studied mobile consumer online information behavior, examining how different information types affect consumer perception and modeling consumer search behavior processes.

2.2 Network Search System Selection and Switching

Network search systems constitute important components of online information sources. Most online information sources have internal search functions, and their content can also be searched through search engines. In this sense, most online information sources are network search systems.

Information source research indicates that with rapid network technology development, many new network search systems continuously emerge. When facing search tasks, users no longer limit themselves to search engines but generally select multiple types of information sources to complete tasks. Y. Zhang et al. [2] studied factors influencing user selection between traditional search engines and other internet information sources in health information seeking contexts through interviews, with statistical results showing participants selected 6-15 information sources (averaging 11). D. Choi et al. [3] conducted user experiments with two groups to examine differences in user information behavior between search engines and social media websites during exploratory search. Results showed that although users of social media websites discovered fewer documents and less document diversity than search engine users, they found more relevant documents and reported lower workload and perceived difficulty.

User preferences for each information source type vary, with factors such as usage experience, education level, and information literacy influencing source selection. Y. Zhang et al. [16] recruited volunteers from campuses, social Q&A platforms, online health communities, and crowdsourcing sites for questionnaire surveys, finding that 84.3%, 46.2%, 19.8%, 6.2%, and 1.2% of users respectively selected search engines, social Q&A platforms, online health communities, social websites, and crowdsourcing sites to solve exploratory tasks. The study also found positive correlations between information system usage experience and selection of search engines, social Q&A platforms, online health communities, and social websites. Y. Sun et al. [17] analyzed how user personal traits affect online information source selection across three health search task types (factual, exploratory, and personal experience), finding that information preferences influenced users' adoption of social network information sources during exploratory tasks, while extroverted personality influenced search engine selection for personal experience tasks. In exploratory tasks, although search engines remained the primary source (95.9%), online health communities and social Q&A platforms were selected by 82% and 57.6% of users respectively, with social websites chosen by 25.9%. Wang Fang et al. [18] systematically reviewed information source selection research, comprehensively summarizing theoretical elements affecting source selection from dimensions of information sources, tasks/environment, and information seekers, and constructed an integrated theoretical model of information source selection.

As mobile search segments vertically, users' search entry points show diversified development trends [19]. L. Bowler et al. [20] studied teenagers' information search behavior and mobile technology, noting that mobile information sources have become embedded in daily life. Teenagers in the study rarely mentioned pure text web resources but instead used social media, applications, and games as information sources, combining search engines with smartphones or tablets for searching, with YouTube serving as an important information source. Zhang Min et al. [21] found in studying mobile medical information search behavior that users generally only used search engines for factual tasks, but for explanatory and exploratory tasks, users supplemented search engines with Zhihu, Weibo, and other vertical medical apps (such as Chunyu Doctor). J. J. Womack et al. [22] noted that pregnant women increasingly use mobile applications as supplementary information sources beyond interpersonal sources, with nearly 300 apps appearing in both Google Play and Apple App Stores when searching for "pregnancy"-related keywords, reflecting substantial demand for specialized vertical applications across domains.

Research on search system switching has primarily focused on search engine switching [4, 23, 24], with less attention to switching between different categories of search systems. Studies show that users often habitually rely on a particular search engine for specific tasks, with search engine switching behavior highly dependent on task characteristics. Theories including psychological motivation theory, communication uses and gratifications theory, innovation diffusion theory, and the technology acceptance model from information systems have been applied to explain or predict user search engine switching behavior.

2.3 Literature Review Summary

Existing studies have extensively examined user mobile search behavior and mobile search system usage, as well as network search system selection, preferences, usage, and switching behavior. However, researchers have limited users' search system usage behavior to one or a specific category of search systems, requiring single selections among numerous options. In real scenarios, mobile users simultaneously have many choices and employ complex search behaviors using multiple different search systems to meet information needs. This study broadens research perspectives on mobile search system usage by examining cross-system search behaviors.

Previous research on network search system switching has focused on users abandoning one search system for another, without revealing the complete picture of multiple search system usage in a single search session. Moreover, existing research has primarily studied search engine switching behavior, with less involvement in user behavior when switching between different categories of search systems. Taking network search system usage trails as the entry point can effectively address these limitations, presenting users' complete network search system usage and switching chains and enabling evaluation research on mobile search system usage trails.

3 Research Design

Comparative studies of desktop and mobile user search behavior have found that desktop users employ browsers for all task types (factual, explanatory, exploratory) and tend to start with search engines. In contrast, mobile users (except for factual tasks) use at least two search systems for over half of explanatory and exploratory tasks, with search tool selection affecting user experience [25]. Therefore, mobile users tend to employ more diverse search systems, with more diversified starting points [26], making them more likely to form diverse search system usage trails—aligning with this study's objectives. Consequently, this study restricts the experimental context to mobile devices.

3.1 Experimental Procedure

This study primarily employs user experiments, assigning search tasks to participants and collecting their mobile search system usage data. The experiment consists of three stages:

(1) **Preparation Stage**: Participants receive an experimental manual introducing the entire process and precautions, then complete a pre-test questionnaire collecting basic information and mobile cross-system search experience.

(2) **Execution Stage**: According to task requirements, participants complete search tasks on their smartphones while screen recording.

(3) **Post-Experiment Stage**: After task completion, participants complete a self-report questionnaire and undergo a brief interview. The post-report questionnaire collects evaluations of search tasks and processes, while interviews explore problems encountered and feelings about search system usage.

3.2 Search Tasks

Based on prior research, health and art are common mobile search topics [7, 27]. B. M. Wildemuth et al. [28] collected 834 articles involving user search experiments, with approximately 89 health-related tasks and 68 art-related tasks. Referencing existing research and conducting small-scale pilot experiments, we revised and improved the tasks, finalizing two search tasks (with Task Two adapted from literature [29]). Complex search tasks are defined as tasks containing potential, uncertain solution spaces or method spaces [30], and both tasks in this study meet these criteria. Compared to Task Two, Task One has higher public attention due to its relevance to users' daily work and life, while Task Two involves less familiar knowledge with lower association with users' daily experiences and greater disparity from participants' prior knowledge and information horizons.

Task One (Health Topic):
Recently, the novel coronavirus has attracted worldwide attention. China has made tremendous efforts to control the epidemic, and you are very concerned about this issue, planning to write a report on COVID-19. The report should include the origin, development, impact, and timeline of COVID-19, covering the global pandemic situation. Understand the WHO's naming of the virus and its rationale. Provide detailed descriptions of prevention measures and learn about various efforts in your region to control the epidemic.

During searching, you may use any search system on your phone, and we encourage using multiple systems. You may screenshot useful information for your report and copy it into your document. Your report should be at least 500 words.

Task Two (Art Topic):
This summer, you will take an art history course. As a class assignment, you must write a report on Leonardo da Vinci's works. The report should focus on da Vinci's general background and some of his popular works. Additionally, you should find details about other artists working for the Medici family in Florence while da Vinci painted *The Last Supper* in Milan, identify two artists who might have known Leonardo, and find evidence of their acquaintance. Furthermore, you should identify different painting methods used by da Vinci and explain how these methods influenced later painting styles.

During searching, you may use any search system on your phone, and we encourage using multiple systems. You may screenshot useful information for your report and copy it into your document. Your report should be at least 500 words.

3.3 Participants

To obtain more diverse and richer trails, this study requires participants with high information literacy and extensive experience with various network search systems. The experiment recruited 24 participants (numbered 01-24 according to experimental order), including 8 males and 16 females aged 18-25 from multiple universities (Wuhan University, Sichuan University, Jilin University, etc.) and 16 majors (Information Management and Information Systems, Clinical Medicine, Economics, etc.), all senior undergraduate students. College students represent the primary mobile search user group and are commonly used as research samples [5, 9-11, 13]. Participants from multiple universities and majors provide strong representativeness.

Regarding mobile search frequency, over 85% of users reported daily mobile search usage, with over 50% using mobile search more than 5 times daily. Most participants frequently use mobile search. Over 50% reported regularly using multiple systems on mobile devices to meet information needs, 37.5% occasionally conducted cross-system searches, and only two reported rarely doing so, indicating most participants had mobile cross-system search experience.

3.4 Data Collection and Processing

Data were primarily obtained through screen recordings of search processes, supplemented by questionnaires and interviews. Screen recordings captured search duration, search systems used, usage time and sequence, and queries at one-second granularity.

The search systems in this study include browsers, search engines, and various platforms with information search functions. For data processing, mobile search systems were categorized into seven types based on system nature and content production/distribution characteristics (see Table 1).

Users' search system selection is driven by search motivations, habits, and other factors, while content organization, brand influence, product positioning, and content characteristics also affect choices. Based on search system usage during tasks, users' search trails were simplified into sequences of search system categories to discover cross-system usage patterns.

Mobile device portability typically allows only one search system's information to be displayed on screen at a time. Therefore, screen recordings enabled tracking users' system trails at one-second intervals. Seven search system categories were coded as A, B, C, D, E, F, and G. Trail extension includes two situations: switching search systems (e.g., from category A to G or G to G) and navigating to other pages within the same system (e.g., entering different queries in the same search engine). Table 2 shows partial search system usage by participant 02, with the trail segment coded as: AGAGAGAAF.

3.5 Search Trail Evaluation Metrics and Measurement

Search process evaluation primarily includes simplicity and clarity. Simplicity reflects users' perception of whether their search process was fast and convenient, rated on a 1-5 scale from "very inconvenient" to "very convenient." Clarity reflects whether users clearly understood when to use which search system, rated on a 1-5 scale from "very unclear" to "very clear."

Search result evaluation includes four aspects: richness, accuracy, novelty, and overall satisfaction. According to definitions of complex tasks, the designed search tasks in this study belong to complex tasks with exploratory search characteristics. Existing literature identifies four features of exploratory search: uncertainty reduction, creativity, exploration, and knowledge discovery [29]. Therefore, this study introduces four evaluation metrics for exploratory search performance. Uncertainty reduction indicates decreased uncertainty about the search task and completion methods. Creativity evaluates innovative processes and methods. Exploration assesses the degree of obtaining new information related to the search topic. Knowledge discovery indicates acquisition of new knowledge about the topic. All metrics use a 1-5 scale from "very dissatisfied" to "very satisfied."

After task completion, self-report questionnaires using five-point Likert scales evaluate search topics, processes, results, and exploratory search performance, with higher scores indicating better performance.

For search topics, familiarity and interest levels are measured. Familiarity reflects prior knowledge about the topic, rated 1-5 from "very unfamiliar" to "very familiar." Interest level reflects subjective interest, indicating the effort users are willing to expend, rated 1-5 from "very uninterested" to "very interested."

4 Results and Discussion

Screen recordings detailed participants' search processes. Aggregating all experimental results involved 164 different search systems: 5 search engines, 5 encyclopedia websites, 6 social Q&A platforms, 6 social media platforms, 13 digital libraries, 45 vertical search systems, and 84 information flow platforms. Vertical search systems and information flow platforms dominate numerically, including numerous health information vertical systems (e.g., Baidu Health Medical Dictionary, 51 Doctor, MiaoShou Doctor) and domain-specific systems (e.g., All History, Caixin, Sina Tech). Vertical search systems' professionalism and domain specificity effectively compensate for traditional search engines' breadth-but-lack-of-depth, enabling targeted information integration and precise queries. The most frequently used information flow platforms include video platforms (e.g., Bilibili, Tencent Video), news platforms (e.g., Tencent News, Toutiao), and portal websites (e.g., Hexun, Sohu, government portals). Information flow platforms emphasize content update speed and accuracy, with some systems (e.g., Tencent News, Toutiao, Bilibili) establishing strong brand recognition and cultivating loyal users who actively select them during searches.

4.1 Relationship Between Task Topic and Search System Type

Two search task topics were designed: health and art. Correlation analysis shows task topic significantly correlates with number of search systems used and task familiarity. Table 3 presents basic user search statistics. For Task One, average familiarity was 3.63 (maximum 5), with 11.67 search systems used. Task Two averaged 2.79 familiarity with 8.83 search systems used. The COVID-19 pandemic's relevance to daily life resulted in higher familiarity for the health topic, with numerous systems providing related information through specialized content sections—likely contributing to more search systems used. No participants majored in art history, resulting in lower familiarity for the art topic.

Only 4 of 24 participants showed significant correlations in category usage across tasks, indicating that for most users, search system category usage numbers were not significantly correlated across different task topics. Therefore, task topic itself is the primary basis for search system selection.

Independent samples t-tests examined whether category usage numbers differed significantly between tasks (Table 4). Significant differences exist for categories B (encyclopedia websites), E (digital libraries), F (vertical search systems), and G (information flow platforms). The health task used more F and G systems but fewer B and E systems compared to the art task, while A (search engines), C (social Q&A platforms), and D (social media) showed no significant differences.

Users employed more vertical search systems and information flow platforms for Task One because: (1) China's mobile health industry has developed rapidly under national policies and public demand, producing numerous health information vertical systems [31]; (2) The COVID-19 topic's evolving nature requires exploring the latest information, and information flow platforms' high timeliness enables rapid response to hot topics. Existing research found that during the pandemic, public information sources primarily included WeChat, official accounts, and media websites/mobile clients [32]—all belonging to information flow platforms and vertical search systems.

Task Two users employed more encyclopedia websites and digital libraries because: (1) The art history topic is static with low timeliness requirements; (2) Lower familiarity (2.79 vs. 3.63) and higher non-routine nature [33] meant users lacked relevant knowledge, biasing them toward structured, accurate sources like Baidu Baike, CNKI Mobile, and personal digital libraries. Digital libraries' long update cycles made them unsuitable for current hot topics, while information flow platforms' focus on speed made them less suitable for historical topics. This demonstrates that users select different search system categories based on topic characteristics.

4.2 Extraction of Mobile Search System Usage Trails

4.2.1 Search System Usage Trail Extraction Example Using participant 02's Task One trail as an example: AGAGAGAAFA AAAFAAGAAGAFAGG

GGGGG. Table 5 shows the search system transition frequencies, where numbers indicate transitions from one system category to another.

To reflect users' preferences for search system types and transition patterns, transition proportions (P) represent the ratio of specific transitions to total transitions. Table 6 shows participant 02's transition proportions, where 0.172 indicates that transitions from G to A accounted for 5 of 29 total transitions (PGA = 5/29 = 0.172), with all proportions summing to 1.

4.2.2 Search System Usage Trail Pattern Analysis Section 4.1 analysis shows no significant correlation in search system usage types across tasks, while task topic significantly affects usage types. Since search system usage trails are sequences of system categories, clustering was performed separately by task topic.

Search system usage trail patterns should reflect preferences for specific systems (usage numbers) and system switching methods. K-means clustering was performed based on transition direction proportions. Hierarchical clustering with between-groups linkage and squared Euclidean distance initially suggested 3-4 clusters. K-means clustering determined K=3 for both tasks. Table 7 shows clustering results.

(1) Task One Clustering Results Analysis
Task One trails cluster into three patterns: Search Engine-Information Flow Platform Biased, Social Media Dependent, and Social Q&A Platform Dependent.

a. Search Engine-Information Flow Platform Biased
This most common pattern for health information is characterized by primary use of search engines and information flow platforms, with main transitions being the four combinations between them (A→A, A→G, G→A, G→G) and minimal use of other types. Cluster centers show PAA = 0.06, PAG = 0.05, PGA = 0.03, PGG = 0.62, indicating approximately 76% probability of transitions between search engines and information flow platforms. High PAA reflects continuous query modification before clicking search results. High PAG and PGA indicate back-and-forth movement between search engines and information flow platforms. High PGG shows continuous query modification or sustained clicking within information flow platforms. As noted, information flow platforms' high timeliness makes them excellent sources for health topics, reflecting a balance between information needs and system supply.

b. Social Q&A Platform Dependent
This pattern features social Q&A platforms as the primary information source, with main transitions completed within this category (C→C). Cluster centers show PCC = 0.63, with other transition types dispersed.

c. Social Media Dependent
Similar to the social Q&A platform pattern but dependent on social media,

with main transitions within social media (D→D). Only three users exhibited this pattern, all showing clear dependence on social media (Weibo). Cluster centers show PDD = 0.73, indicating over 70% of transitions occurred within social media. In interviews, these users identified as loyal social media users who knew needed information existed there, reflecting how search habits and experience influence trail patterns.

(2) Task Two Clustering Results Analysis
Task Two trails cluster into three patterns: Search Engine Dominant, Search Engine-Encyclopedia Website Biased, and Social Q&A Platform Dependent.

a. Search Engine Dominant
This most common pattern for art tasks features search engines as the hub, with transitions from search engines to other systems and back (A→N and N→A, where N represents any system type). Cluster centers show PAN + PNA = 0.873, indicating continuous back-and-forth between search engines and other systems. This likely emerges from low topic familiarity, leading users to select traditional, comprehensive search engines as the primary system.

b. Search Engine-Encyclopedia Website Biased
This pattern features combined use of search engines and encyclopedia websites, with main transitions being the four combinations between them (A→A, A→B, B→A, B→B). Cluster centers show PAA = 0.176, PAB = 0.219, PBA = 0.210, PBB = 0.122. High PBB reflects continuous switching between encyclopedia entries. Since the topic involves famous figures and works with independent entries in encyclopedia websites—often appearing first in SERPs with strong structure, accuracy, and convenient interlinking—users 偏向 these two system types.

c. Social Q&A Platform Dependent
Similar to Task One, this pattern shows dependence on social Q&A platforms, with cluster centers showing PCC = 0.406. This pattern appears in both tasks with identical characteristics, likely because social Q&A platforms organize information by questions/topics through crowdsourced content creation and community voting-based ranking (e.g., answer counts, upvotes, downvotes, comments) [34], making topic characteristics less influential while answer quality matters more.

4.3 Evaluation of Mobile Search System Usage Trails

Clustering by task topic yielded three patterns each, but both tasks included the Social Q&A Platform Dependent pattern with identical features. Therefore, five total patterns are identified: Search Engine-Information Flow Platform Biased, Social Media Dependent, Social Q&A Platform Dependent, Search Engine Dominant, and Search Engine-Encyclopedia Website Biased. Different patterns show distinct characteristics in system selection and usage sequences, evaluated from three aspects: search process, search results, and exploratory search performance.

4.3.1 Search Process Evaluation Table 8 shows user evaluations of search tasks and processes. While task familiarity and interest are not evaluation criteria, they partially explain pattern emergence.

Social Media Dependent shows highest task familiarity and highest simplicity and clarity scores, despite lower interest levels. Users with this pattern had relevant search experience, knew information locations, and found the process simpler due to lower interest and less active exploration.

Search Engine Dominant shows lowest task familiarity and lowest process simplicity. Low familiarity led users to traditional search engines as the main system, continuously switching between search engines and other systems, resulting in low simplicity. Lack of topic knowledge and understanding of effective information distribution also yielded low clarity.

Social Q&A Platform Dependent ranks second in simplicity and clarity (after Social Media Dependent), with highest interest levels and stronger information-seeking initiative. Search Engine-Information Flow Platform Biased shows moderate evaluations across all dimensions.

Search Engine-Encyclopedia Website Biased shows lowest interest and clarity levels, with users unclear about when to use which system, consequently concentrating on highly structured encyclopedia websites.

4.3.2 Search Results Evaluation Search results evaluation includes richness, accuracy, novelty, and satisfaction. Figure 1 [Figure 1: see original paper] shows ratings across patterns.

Social Media Dependent achieves the best ratings on all four indicators, with only three samples but very high evaluations. These users had relevant search experience and background knowledge, noting in interviews that social media offers "rapidly updated first-hand information."

Search Engine-Information Flow Platform Biased ranks second, with accuracy and novelty 仅次于 Social Media Dependent but lower richness and satisfaction than Social Q&A Platform Dependent and Social Media Dependent.

Social Q&A Platform Dependent ranks third, with richness and satisfaction 仅次于 Social Media Dependent but lowest accuracy and moderate novelty. This pattern's reliance on social Q&A platforms makes accuracy difficult to verify.

Search Engine Dominant ranks fourth on all four indicators, showing no distinguishing features in search results.

Search Engine-Encyclopedia Website Biased performs worst, with lowest richness, novelty, and satisfaction but relatively good accuracy.

4.3.3 Exploratory Search Performance Evaluation Exploratory search features four characteristics: uncertainty reduction, creativity, exploration, and knowledge discovery [29]. Figure 2 [Figure 2: see original paper] shows performance across patterns.

Social Media Dependent shows best overall performance. Search Engine Dominant, Social Q&A Platform Dependent, and Search Engine-Information Flow Platform Biased show similar performance with minimal gaps. Search Engine-Encyclopedia Website Biased performs worst.

For uncertainty reduction, Social Media Dependent performs best while Search Engine-Encyclopedia Website Biased performs worst. Creativity (evaluating innovative information-seeking methods) is highest for Social Media Dependent, second for Search Engine-Encyclopedia Website Biased, and lowest for Search Engine-Information Flow Platform Biased. Exploration (degree of obtaining new information in defined domains) is best for Social Media Dependent, followed by Search Engine Dominant, Social Q&A Platform Dependent, and Search Engine-Information Flow Platform Biased, with Search Engine-Encyclopedia Website Biased worst. Knowledge discovery is best for Search Engine Dominant, followed by Social Media Dependent, Social Q&A Platform Dependent, and Search Engine-Information Flow Platform Biased, with Search Engine-Encyclopedia Website Biased worst.

4.4 Discussion

This study examined mobile search system usage trails, revealing new characteristics compared to PC-based information seeking behavior research [24, 35-36]. Mobile search sessions involve multiple search system types with continuous cross-system characteristics, including entering identical queries across different systems or constructing queries in one system based on results from another. Compared to PC's browser dependence, mobile users are more sensitive to information types, actively selecting corresponding search entry points for video resources, UGC resources, or domain-specific resources. Task familiarity affects search behavior and even habitual behavior, particularly evident in search system usage—users with high familiarity employ specific systems based on experience to locate needed information accurately.

Compared to existing information source selection research, this study focuses on network search systems used on mobile devices, expanding source classification by adding "information flow platforms" as a new category. Toutiao, WeChat Official Accounts, and other information flow platforms are frequently used on mobile devices, with usage frequency far exceeding PC 端. Similarly, mobile Q&A platforms like Zhihu APP are accessed more frequently than PC 端. In this study, users employed 84 different information flow platforms, accounting for 51.22% of all mobile search systems—a significant difference from PC search system distribution [20, 37].

Regarding search entry points, PC users primarily rely on search engines with multiple types [25, 38]. In this study, only four participants used search engines exclusively (with three using two different search engines). Beyond search engines, 18 participants (75%) used other system types as entry points for Task One, and 14 participants (58%) did so for Task Two. This indicates more diversified search entry points on mobile devices, contrasting sharply with PC 端's search engine dominance.

Categorizing mobile search systems by content production and distribution characteristics (rather than information domain) reveals that users show significant preferences for different system types across topics and exhibit specific usage trail patterns. Previous research categorizing by information domain found unclear correlations between some topics and system types [9]. This suggests mobile users focus more on content production/distribution characteristics than professional domains when selecting search systems. In the fast, convenient internet era, information dissemination is extremely simple, and information homogeneity is high within the same professional domain. Therefore, search systems should emphasize improving user search experience and building distinctive information search platforms.

This study's theoretical contributions include: (1) proposing the concept of search system usage trails and extraction methods, enriching information search behavior research theory; (2) establishing a multi-dimensional evaluation system for search trails, providing theoretical foundations for candidate trail selection in trail recommendation.

Practical implications include: (1) mobile search systems (apps) can provide diverse search functions and experiences based on trail characteristics to reduce system switching; (2) design task-oriented search interfaces integrating multiple mobile search system types to provide integrated search environments for task-based activities; (3) evaluation metrics and results can guide trail recommendation and provide search assistance services.

Limitations include: (1) trail evaluation metrics rely primarily on subjective ratings, requiring development of more objective measures; (2) limited participant numbers and task scenarios may affect conclusions, necessitating larger-scale experiments across more scenarios for validation and generalization.

Future work includes: (1) further refining search system usage trail evaluation metrics; (2) conducting larger-scale user experiments to discover more trail patterns; (3) investigating task scenario impacts on trail patterns; (4) developing corresponding trail recommendation systems.

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Author Contributions

Zhao Yiming: Conceptualization, methodology, writing—original draft, writing—review & editing.
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Extracting and Evaluating User Search Trails on Mobile Search Systems

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Abstract: [Purpose/Significance] This study extracts users' complete trails of search system usage and switching on mobile devices, revealing differences in process and outcomes among various mobile search system usage trails. [Method/Process] This paper adopted experimental research methods, combined with questionnaires and interviews, and designed complex search tasks under two different topics. From the perspective of mobile search system usage, search systems were treated as nodes to form users' search trails on mobile search systems, and the cluster analysis method was used to discover and summarize specific patterns of those trails. Each specific pattern of those trails was evaluated and analyzed from three aspects: search process, search results, and exploratory search performance. [Result/Conclusion] Mobile users have preferences for the search system under different task topics while specific patterns of user search trails on mobile search systems exist. There are differences in users' evaluation on the search trails on mobile search systems under different patterns.

Keywords: mobile search, search system, search behavior, search trail, search trails on search systems