Understanding the Paths and Patterns of App-Switching Experiences in Mobile Searches

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Abstract: Mobile searches have become the main channel for people to search for information, and mobile searches have received attention in the field of information-seeking behavior. Especially as users use various apps to search network information, the app-switching behaviors in mobile searches have also attracted scholars’ attention in recent years. Research on app-switching behaviors in mobile searches can help to further understand users’ search motivations, evaluate search results, and improve users’ mobile search experiences. This study recruited participants (n = 30) and conducted a 15-day user experiment. This study collected all participants’ mobile phone log data during the experiment and identified the app-switching behaviors in mobile searches through a log collection tool. This study aimed to discover the app-switching behavior paths and patterns in mobile searches. Firstly, the basic characteristics of app-switching behaviors in mobile searches were analyzed, as were the app-switching paths in mobile searches from the perspective of switching probability between apps. Then, the different behaviors in mobile search sessions were identified and app-switching behavior patterns were put forward. These behavior patterns summarize user behavior changes in mobile search sessions. This paper focused on analyzing app-switching behavior paths under different patterns and found apparent differences in app-switching behavior paths. This study examined mobile search behavior from the perspective of app-switching. The research of this paper can help to better understand the relationship between users’ mobile search behaviors and app interactions and is an excellent supplement to the analysis of mobile search behaviors.

Keywords: information-seeking behavior; mobile search behavior; information behavior; mobile app; app-switching behavior

1. Introduction

With the development of smart mobile devices and information communication technology, the mobile Internet has played a more important role in the economy and culture, and in people’s lives. According to the marketing statistics from Smart Insights [1], mobile Internet traffic will continue to increase in the future. It has become the primary way people access network information through smartphones. Mobile searching has become an important way for people to obtain information in the mobile Internet environment. The number of mobile search users in China has reached 795 million [2].

In recent years, mobile searching has also become a hot topic for scholars. Kamvar and Baluja [3] conducted mobile search research and analyzed more than one million Google mobile search engine log data, and they explored users’ mobile search needs through query topics. Baeza-Yates et al. [4] compared the mobile search queries of Japanese and American users, finding that users from different countries have differences in query topic distributions. In mobile searches, the users’ search tasks will span multiple search sessions, and the users will continue to restore the previous search task after a period of time [5].
Spink et al. [6] studied query formulation in a single search session and switching between tasks or multitasking information behaviors. In addition, the previous research [7] analyzed the users’ good abandonment behaviors in mobile searches through an eye movement experiment. It proposed a model to evaluate the reliability, which is beneficial for assessing mobile searches.

With the rapid development of the mobile application (app), users’ mobile searches present new characteristics, which are mainly reflected in that various apps have become new channels and platforms for users’ mobile searches. The behavior of users interacting with different apps has become the focus of information behavior research [8].

In a mobile search scenario, users’ search tasks are more closely combined with local services and social networks [9]. For example, users search news on YouTube and share it on Facebook. In this case, a user’s search behavior occurs on different apps, which is called “app-switching behavior” [10]. Figure 1 shows a user’s interaction in a search session. He/she first used Spotify to search for “Sugar”. After listening to the song, he/she searched a video on YouTube with the query “Sugar maroon”. Then he/she used Facebook to share the video and switched to TikTok. In this search session, the user conducted activities such as submitting queries and sharing search results with different apps. Figure 1 shows an example of actual app-switching behavior.

![Figure 1. Example of app-switching behavior in mobile searching.](image)

Existing studies have found that when users use mobile phones, they often switch from an initial app to other apps [11]. Especially in the mobile search context, users often use multiple apps in one search session [12]. After a user enters a query, a series of follow-up activities will occur to interact with the app [13], triggering app-switching behavior in mobile searching. In addition, the switching behavior between different apps has also attracted scholars’ attention. Liu et al. [14] studied users’ switching behaviors on a question and answer platform. A dissatisfaction with the quality of information could trigger users’ switching behavior. In addition, burnout will affect whether users’ switch to other mobile instant messaging (MIM) apps [15]. Scholars have also analyzed users’ app-switching behaviors and proposed a method of predicting the next app to be used [16].

User behavior paths have always been the focus of research on app-switching behavior in mobile searches. The app-switching path can be regarded as a user’s choice of information systems or information sources. Different apps play different roles in users’ mobile searches [17]. The research on app-switching behavior in mobile searches can help us better understand the behavioral characteristics of users in mobile searches. Further, it can help us better understand why users switch apps in mobile searches and find the association between different apps.

Further, researchers can predict users’ future app use according to the distribution of users’ app-switching paths. These efforts can improve a user’s search experience. For example, during a user’s mobile search process, the information system they use can
recommend apps that the users may use next. In addition, it can help different app developers find potential partners and opportunities for business benefits.

Therefore, this paper aims to study the paths and patterns of users’ app-switching behaviors in mobile searches and their relationships. To investigate this problem, we conducted a long-term user experiment to collect mobile search and app interaction data generated by users in daily life. The research questions of this study include:

RQ1: How are the paths of users’ app-switching behaviors distributed in mobile searches?
RQ2: What are users’ app-switching behavior patterns in mobile searches?
RQ3: What is the relationship between a user’s app-switching behavior and the app-switching behavior pattern in mobile searches?

Our research can examine the relationship between users’ mobile search behaviors and app interaction from a new perspective. This paper also extends the app-switching behavior to the mobile search field and to relatively new research in the current mobile search behavior and user information behavior research.

Researching app-switching behavior can help to understand users’ search intentions effectively and to propose a model of app-switching behavior in mobile searches. It also makes effective and accurate predictions and recommendations about users’ app interactions, subsequent behaviors, and search activities in mobile searches. This study can help researchers to provide some references for prediction research.

2. Literature Review

2.1. Mobile Search Behaviors and Mobile App Interactions

With the rise of mobile Internet, mobile search behavior has attracted much attention in academia, including user query formulation, search session, search need, search motivation, search task, search tool, etc. Kamvar and Baluja [18] analyzed the difference between users’ search behaviors on mobile phones and on personal computers. In the research on mobile search queries, it was found that users would input faster on mobile devices, submit multiple times in a short time, and click more search result pages simultaneously [18]. As users own more devices, their search behavior on mobile devices will often be interrupted and they will continue on other desktop devices [19]. On different devices, users’ search needs are different.

User interactions in mobile searches are also a focus of research, especially relating to mobile search sessions and query topic distributions, which play an important role in understanding users’ mobile search needs. When a user performs a mobile search, their interactive session duration with the mobile device is longer, and the types of data collected by the mobile device are more diverse [5]. Sohn et al. [20] found that users’ mobile search needs will change with different situations, and they studied mobile search motivation at other times, in different places and in various social scenarios.

With the rapid development of the app market, various apps play more critical roles in people’s lives. In the information science field, scholars have paid intention to app usage in mobile payment [21,22], mobile app privacy [23], mobile app shopping [24], mobile learning [25], mobile health [26], etc. Users will also interact with different apps during mobile searches [10,27]. The time characteristics of users’ interactions with apps in mobile searches are essential factors. Users often interact more with different types of apps in mobile searches, and some of them last up to 30 min [28]. Users’ interactions with apps also show the characteristics of fragmentation, and Jesdabodi and Maalej [17] found that the average interaction time duration between a user and a single app in a mobile search is approximately 1 min. In addition, the interaction durations between users and apps also changes with time, geographical locations, and social situations. Other studies have found that interaction times are the longest in the mornings and the evenings [12]. In addition, users will have fragmented app usage in mobile searches and social networking [13].

Further, the apps used in mobile searches are also associated with the search topics. In many search sessions, users only use one app, and these search topics are often related to activities such as watching videos, listening to music, and playing games [29]. When
users search for specific content and services in the mobile Internet environment, they will pay more attention to searching local information based on geographical location [30]. However, some scholars have found that users also use different apps when searching for information on the same topic [11].

2.2. Mobile Search Behavior Paths

From the perspective of information system interaction, different apps such as search engines and social media can be regarded as network information systems or information sources [31]. The path of the app-switching behavior reflects the change in a user’s choice of information sources in a mobile search.

Many scholars have studied users’ behavior paths when searching network information, such as switching information sources. Zhang studied users’ behavior paths when searching for health information and found that users chose 6–15 information sources [32]. Users’ search behavior paths will switch between multiple information systems. In exploratory searches, users often select numerous information sources, among which search engines and social media are the primary information sources.

In exploratory search tasks, users’ perceptions of using social media for searches are less complicated [33]. Zhang et al. found that in exploratory searches, users were most likely to choose search engines (84.3%), social question and answer platforms (46.2%), and social networking sites (6.2%), and the user experience would affect the choice of information source [34].

In addition, search tasks often affect users’ search behavior paths [35]. They will choose different search platforms when facing different search tasks [36]. Broder initially divided search tasks into informational, transactional, and navigational [37]. This classification has been widely used in later research. Aliasnejadi et al. found that users are more prone to switching apps when performing informational search tasks [38]. Carrascal and Church [10] found that users’ interactions with other apps will lead them to use more apps in mobile searches, thus triggering app-switching behaviors. Further, apps’ functions are also developing, and mobile searches no longer occur on mobile search engines. In mobile searches, young users, especially millennials, prefer to use different apps such as social media (e.g., Twitter) and streaming media (e.g., YouTube or TikTok) to search with the popularity of smart devices [39].

Scholars have also predicted the paths of using apps in recent years, mainly focusing on predicting which app a user will use next. Predicting app-switching behavior can effectively help to understand user preferences when using different apps [40]. However, current research has mainly focused on app-switching paths under general interaction situations and ignores the app-switching behaviors in mobile searches. A ubiquitous app-switching path is when a user relaunches the initial app [41]. In the existing research on app-switching path prediction, the main method is to collect a user’s log data on a mobile phone. Shin et al. [42] pointed out that because people install more and more apps on smartphones, users will use more and more apps in a session, which challenges the prediction of app-switching paths. Therefore, scholars have begun combining log data and users’ contextual information, such as personalized preferences [43] and geographical locations [44]. Lu et al. [45] proposed discovering the dwell position in a user’s GPS data and to mine the app usage sequence using the sequence algorithm to predict the next app to be used. Some studies indicate a user’s subsequent interaction behavior through time, location, and the app last used [46–48]. Zemla et al. [49] predicted users’ revisitation behaviors by the frequency with which they accessed apps, as well as the users’ contexts.

In summary, users have higher requirements for mobile search experiences in the mobile Internet environment. Switching apps repeatedly in a mobile search will increase the burden of a user. Studying users’ app-switching behaviors in mobile searches and mining their behavior paths and patterns can help predict users’ app usages. However, current research on users’ app-switching behavior paths has not fully considered the scenario of a mobile search. Indeed, a strong correlation exists between app-switching behavior in
a mobile search and a user’s behavior intention. It is not easy to obtain research data on app switching. Some search engines or commercial companies have few apps for their large-scale log data, while users will use many different apps on their mobile phones. For example, Google can provide data from Google Search and YouTube, but obtaining search logs from Facebook and Twitter is challenging. However, a user’s search activities will switch among these apps. The user experiment method may be an option. With the help of professional log data collection tools, researchers can obtain all the app interaction data of users using mobile phones.

3. Research Design

3.1. User Experiment Design and Process

This study was carried out using the log data obtained from a 15-day user experiment. Most of the existing mobile search studies used the questionnaire method to study users’ satisfaction and continuous usage behaviors. The mobile empirical sampling method has recently been widely used in small-scale user experiments. The experience sampling method (ESM) collects, records, and analyzes people’s timely memories of real life [50]. In the mobile search scenario, some scholars have required users to record mobile search queries and their mobile search context information every day to describe their mobile search needs [20]. Other scholars have conducted mobile search research through crowdsourcing experiments. For example, collecting participants to obtain the queries and apps used in mobile searches daily via Amazon MTurk to study their app-switching behaviors in mobile searches [38].

The questionnaire is a standard empirical research method. However, this method cannot collect the log data of smartphone interactions in natural environments. Large-scale log data provides good support for user behavior research, but anonymous user data is challenging for conducting in-depth cause analyses for specific user behaviors.

To answer the research questions of this paper, we need to collect users’ actual and daily mobile search data as much as possible. In addition, we hope the collected data can reflect specific users for conducting an in-depth behavioral motivation analysis combined with log data. Therefore, we designed a mobile search user experiment in a natural scene. Unlike the experimental tasks specified for users in a controlled experimental study, this study does not design or set any practical tasks for users. We obtained mobile search behavior data in users’ daily lives through a professional log data collection tool. Then, we analyzed the paths and patterns of app-switching behaviors in mobile searches. Specifically, the user experiment in this study included the following processes.

3.1.1. Participants’ Recruitment

In existing studies using user experiments, 20–30 participants are considered appropriate [5,13,51,52]. Particularly for long-term experiments, this number of participants can produce enough rich research data.

This study recruited potential participants on social networks through a pre-test questionnaire, which collected the user’s background information, such as age, education, mobile phone brand, and model, and the user’s daily mobile search experience. This study selected users with high frequencies of everyday mobile search experience as participants, which was intended to help collect rich data.

A total of 30 participants were recruited, including twenty-one females and nine males. The participants included college students, IT employees, teachers, and other occupations. The participants’ educational backgrounds included 13 majors, such as financial management, engineering, history, information systems, etc. Most participants had installed more than 40 apps on their smartphones and had rich app-switching behavior experiences.

In this study, we also needed to protect user data privacy. When recruiting participants, we introduced the data to be collected to all participants. We also signed a privacy protection agreement with all participants, ensuring that the users could delete their sensitive data,
especially their chat content on social apps. The participants could also choose to stop participating in the experiment at any time. The user data collected in this study was only used for scientific research and has not been disclosed, protecting the personal privacy of all participants. Each participant could receive RMB 300 after the whole experiment was completed.

3.1.2. Pre-Experiment

After recruiting participants, we trained them and installed the log collection tool—AWARE—on their smartphones. This tool will be introduced in Section 3.2. The participants were asked to be familiar with the AWARE operation in the pre-experiment stage and to learn to send daily log data to the researchers.

3.1.3. Fifteen-Day Experiment

After the pre-experiment stage, all participants began a 15-day formal experiment. During the 15-day experiment, we did not require the participants to complete specific experimental tasks. Except for sending log data to the researchers daily, all participants were not disturbed during the experiment. It ensured the authenticity and objectivity of the log data collection.

During the experiment, each participant was asked to keep AWARE running. Every night, we asked the participants to find the log data documents on their smartphones and send them to us. Through the above measures, we ensured that the log data generated by each participant during the experiment was real and complete.

3.2. Mobile Log Data Collection

Although the large-scale log data of search engines have advantages in data volume, they cannot track every specific user, and so it is not easy to analyze the in-depth reasons behind a particular user’s behavior. Therefore, we chose AWARE [53], a smartphone log record tool, to collect participants’ smartphone log data during the experiment. AWARE can operate on Android and iOS smartphones, and it contains the data of smartphone interaction logs by acquiring the privileges of different sensors of smartphones. These log data can be saved locally on the mobile phone or the cloud server.

The advantage of AWARE is that it can obtain the interactive data of users on all apps when using smartphones, which supports this paper in studying the users’ app-switching behaviors in mobile searches. AWARE cannot collect mobile phone screenshots, user accounts, and passwords. AWARE mainly records the time of use of each app, the app name, the text input to the app, and other information, which could help us identify the users’ mobile search behaviors and app-switching behaviors. Table 1 shows the log data contained in the AWARE dataset.

Table 1. The log data content in the AWARE dataset.

| Data Field         | Field Type | Description                   |
|--------------------|------------|--------------------------------|
| id                 | INTEGER    | Data record number            |
| timestamp          | REAL       | Data record time              |
| device_id          | TEXT       | Mobile phone identification code |
| application_name   | TEXT       | App name in users’ smartphones |
| current_text       | TEXT       | The user’s text input         |
| is_system_app      | BOOLEAN    | 0: non-system app; 1: system app |
| is_password        | INTEGER    | 0: non-password, 1: password  |

In the 15-day experiment, participants could check the log data before sending it to the researchers. The researchers could also check whether the participants had turned off AWARE by the time in the log data. According to the frequency of the participants
using smartphones during the pre-experiment, it was found that all the participants would not use mobile phones for more than five hours during the non-rest period. Therefore, if there was no log data for more than five consecutive hours in the 15-day experiment in the non-rest period, the researchers would check the AWARE operation to ensure the enrichment of user data. In total, we received 15 (participants) × 30 (days) of log data.

3.3. Identification of App-Switching Behaviors in Mobile Searches

By analyzing the time, text content, app name, and other information in the log data collected by AWARE, this study explored the app interaction behaviors after the participants submitted the queries and identify the users’ app-switching behaviors in mobile searches.

The query is the text content submitted by a user when searching for information. It reflects the information needs of a user, to a certain extent. The researchers manually analyzed the text content and the corresponding app information to determine the queries of the log data. Referring to previous studies [12,13], this paper used a 5-min time gap to divide mobile search sessions.

After the users submitted the queries in the search sessions, various interactive behaviors would occur on the app. We analyzed the apps used by the participants in the log data to identify the app-switching behaviors in mobile searches. In the case where a participant switched to another app from the initial app in one search session after submitting the query (on the initial app), it was considered that one app-switching behavior had occurred.

4. Findings

4.1. App-Switching Behavior Statics

In real life, users will use a large number of apps. Due to many of these apps not being convenient for statistical analysis, this paper classified all the apps used by the participants during the mobile search. Because the smartphones used by the participants were Android systems, this study selected the app category of GooglePlay to divide all the apps used by participants into 26 different types, as shown in Figure 2.

![Figure 2. Types of apps used in the mobile searches.](image)

Participants primarily used communication apps in mobile searches, reflecting the relationship between users’ mobile searches and their communication behaviors. In addition, Figure 2 shows an obvious long-tail effect; that is, many mobile searches occurred on only a few types of apps.
According to the app-switching behavior identification method, a total of 8518 app-switching behaviors were identified in all the mobile search sessions. The x-axis in Figure 3 represents the number of app-switching behaviors in a mobile search session. The proportion of mobile search sessions with one app-switching behavior is the highest (25.35%), and the ratio of mobile search sessions with 1–5 app-switching behaviors is as high as 76.44%.

![Figure 3. Counts of app-switching behaviors in the mobile search sessions.](image)

4.2. App-Switching Behavior Paths during The Mobile Searches

This section analyzed users’ app-switching paths in mobile searches, primarily from the switching probabilities between different apps. This study first analyzed the specific app-switching paths between other apps, and then it analyzed the app-switching paths between different app types.

4.2.1. App-Switching Behavior Paths between Different Unique Apps

The app-switching path refers to the probability that a user will use one app to perform app-switching behavior and switch to other apps in a mobile search session. Due to switching between different apps, a directed switching network can be formed. This network structure can more intuitively reflect the switching behavior between different apps.

This study constructed an app-switching network in mobile searches through the social network analysis software Gephi 0.9.2. In this network, the app used before the app-switching behavior was regarded as the source node, and the app used after the app-switching behavior was regarded as the target node. An app-switching behavior is formed from a source node app to its corresponding target node app. The average degree of social networks among the different apps is 6.742, and the moderate weighting degree is 28.205. The average clustering coefficient is 0.434, and the average path length is 2.667.

Among all the unique apps, the following app-switching paths had high probabilities: “QQ → WeChat” (2.49%), “Mobile Taobao → WeChat” (2.39%), “Baidu → WeChat” (2.09%), “Baidu → QQ” (1.94%), “Sina Weibo → WeChat” (1.89%), and “WeChat → Mobile Taobao” (1.87%). This also reflects that the use of social apps often accompanies mobile searches.

4.2.2. App-Switching Behavior Paths between Different App Types

The previous section analyzed the app-switching behavior paths between different unique apps. Due to the existence of many unique apps, there are too many nodes in Figure 4, and we cannot effectively find the app-switching path characteristics between the different types of apps. Therefore, this section focuses on the distribution of app-switching behaviors among the different app types.
Interestingly, we can see that the app switching on some apps that did not account for a high proportion (such as finance apps) almost always led to switches to communication apps. When users firstly searched in communication apps, they were more likely to switch to other types of apps than to a similar one. This reflects that in mobile searches, users will interact with more apps in complex ways. This presents a challenge in studying the users' behavioral characteristics.

4.2.3. App-Switching Behavior Paths in the Mobile Search Sessions

In the previous sections, we discussed how users will often use multiple apps in search sessions. We further analyzed the evolution of app-switching behavior paths in mobile searches. In this study, the first app used by participants in a mobile search session is represented by $A$, and the second app is represented by $B$. The first app-switching behavior occurred between apps $A$ and $B$, but a user might continue switching to other apps.

Among the 8518 app-switching behaviors, 7204 (84.57%) occurred between different types of apps. For example, when participants switched from the Apple Music app to the YouTube app, they switched from music apps to video apps. Other app-switching behaviors occurred in the same type of apps. For example, the switching from the Taobao app to the Amazon app was switching between shopping apps.

Studying the types of apps in app-switching behaviors can help understand users' preferences for information sources. This paper draws the Sankey diagram in Figure 4, according to the app data in the all app-switching behaviors, to clearly show the app-switching behavior paths between the different app types. Figure 4 reflects the proportion of different types of apps before and after switching behaviors in mobile searches and the directions and probabilities of app-switching behaviors between other apps. The left column in the figure represents the app types used before the app-switching behavior. The right column represents the app types used after the app-switching behaviors. The scale length in Figure 4 represents the frequency distribution of such apps before app switching.

Figure 4. App-switching behavior paths in mobile searches.

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The data flow in the figure represents the number of app-switching behaviors switched from app types in the left column to the app types in the right column.

The results in Figure 4 show that tool, communication, social, and shopping apps account for a high proportion of the before the app-switching behaviors in mobile searches. Among them, the tool apps triggered app-switching behaviors to other 25 different types of apps. After the app-switching behaviors in mobile searches, the proportion of communication app usage was the highest, reflecting that communication apps were often the preferred app types after the app-switching behaviors, followed by tool apps, social apps, shopping apps, etc.

In addition, when the participants used tool apps, the app-switching behaviors mainly occurred with communication apps. App-switching behaviors on social apps largely saw switches to communication apps. Further, the probability of communication app-switching to using tool apps, social apps, shopping apps, and music audio apps was high. App-switching behaviors on music and audio apps largely saw switches to communication apps, tool apps, social apps, etc.

Interestingly, we can see that the app switching on some apps that did not account for a high proportion (such as finance apps) almost always led to switches to communication apps. When users firstly searched in communication apps, they were more likely to switch to other types of apps than to a similar one. This reflects that in mobile searches, users will interact with more apps in complex ways. This presents a challenge in studying the users’ behavioral characteristics.

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![Figure 5. Paths of app-switching sequences in the mobile search sessions.](image-url)

From the perspective of app sequences in app-switching behaviors, there are many "revisitation" paths. In 76.44% of the experiment’s mobile search sessions, participants used up to six different apps. This paper records the sequences of apps used as A, B, C, D, E, and F. Figure 6 shows the paths of the app-switching sequences in the mobile search sessions. That is, the participant used app A, then switched to app B, and then returned to using app A.
4.3. App-Switching Behavior Patterns during Mobile Searches

4.3.1. Different Behaviors in Mobile Search Sessions

As mentioned above, in a mobile search session, in addition to submitting queries, a user will browse search results, share search results, and continue using other apps and perform other activities. Therefore, there are different behavior types in a search session. In this study, combined with the data collected by AWARE and that of previous studies, the participants’ behavior types in mobile search sessions are divided into three types:

1. **Searching input behavior (Search).** This refers to using an app to enter text and search for network information through a smartphone’s keyboard. In a search session, the initial behavior type is *Search*.

2. **Other inputting behavior (Input).** This includes all the behaviors that require text input contents, such as social chatting, taking notes, storing information, etc. Other than *Search*, the rest of the behavior types belong to this type.

3. **Browsing or using app behavior (App Usage).** AWARE cannot capture the screen of a user’s mobile phone. Therefore, in the log data, when a user unlocked their phone, the log data other than the *Search* and *Input* behaviors was regarded as *App Usage*.

4.3.2. App-Switching Behavior Patterns in the Mobile Search Sessions

Based on the above, this study proposed an app-switching behavior pattern in mobile search sessions according to the distribution of user behavior patterns. As shown in Figure 6, when a user starts to use an app, the first judge is whether the user inputs content and whether that content is the query. It can determine a user’s behavior with the first app. When a user starts to use another app, the judgment process is repeated to identify the user’s patterns in app-switching behaviors.

There are nine different paths for the changes in the patterns of app-switching behavior: (1) Search → Search; (2) Search → Input; (3) Search → App Usage; (4) Input → Search; (5) Input → Input; (6) Input → App Usage; (7) App Usage → Search; (8) App Usage → Input; and (9) App Usage → App Usage.

This paper mainly studied the app-switching behaviors in mobile searches, focusing on users’ behavior patterns after submitting their first query in a mobile search session. When a participant submitted an initial query on the first app in the search session, their behavior for the next app had three different types: *Search, Input*, and *App Usage*. The following sections of this paper are also focused on the following three app-switching behavior patterns: (1) Search → Search; (2) Search → Input; and (3) Search → App Usage.

![Figure 6. App-switching behavior patterns in mobile search sessions.](image_url)

4.3.3. Time Characteristics of the App-Switching Behavior Patterns of Mobile Searches

This section analyzes the interaction duration between the participants and the apps under three different behavior patterns (*Search → Search; Search → Input; and Search → App Usage*).
Usage). As shown in Figure 7, the interaction time with an app used by participants after app-switching behaviors is longer.

![Interaction time duration (seconds) before and after app-switching behavior.](image)

**Figure 7.** Interaction time duration (seconds) before and after app-switching behavior.

The interaction time on an app before app-switching behavior is the shortest, while the interaction time after app-switching behavior is the longest. Especially in the “Search → Search” behavior pattern, there is a noticeable gap in the interaction time before and after the app-switching behavior in a mobile search. This reflects that the first search input behavior (Search) did not help participants find relevant search results. Participants decided to replace other apps in a short time and submit queries again for further searches. After submitting the query to the next app, the interaction time with the app increased significantly, reflecting that the participants found information that was more in line with their needs. 

In the “Search → App Usage” pattern, the interaction time before and after app-switching was long. In this pattern, participants spent the longest time (44.82 s) searching on the first app before beginning app-switching behavior.

In the “Search → Input” pattern, the interaction time with the app used before and after app-switching behavior was short. Especially after app-switching switching, the following interaction duration with an app was the shortest in three different patterns. Combined with the evolution trend shown in Figure 5, participants may switch to other apps again after engaging in Input behavior.

4.4. Relation between App-Switching Behavior Paths and Patterns

This paper focused on app-switching behaviors in mobile searches, and so it mainly analyzed the behavior patterns after submitting a first query in a mobile search session. This section focuses on the app-switching behavior path triggered by Search behavior.

4.4.1. App-Switching Behavior Paths in the “Search → Search” Pattern

In the “Search → Search” behavior pattern, 21.57% of the app-switching behaviors led to switches from social apps to tool apps, and 13.73% led to switches from tool apps to social apps. In this behavior pattern, the correlation between social and tool apps is most potent, as shown in Figure 8.

Before the app-switching behavior in this pattern, the most apps used by participants were social apps, tool apps, and shopping apps. Tool and shopping apps increased the behavior of switching to other types of apps. Only 3.92% of shopping apps use led to switches to the same type of apps, and more app-switching behaviors led to switches to social, travel, local, education, and tool apps.
4.4.2. App-Switching Behavior Paths in the "Search → Input" Pattern

In the "Search → Input" behavior pattern, communication apps were the most frequently used when the participants performed app-switching behaviors in mobile searches. In this behavior pattern, 86.84% of app-switching behaviors led to switches to communication apps, of which the WeChat app and the QQ app account for the majority. The proportion of app-switching behaviors that switched to communication apps was high: for tool apps it was 23.68%, for social apps it was 16.67%, for education apps it was 15.79%, and for travel and local apps it was 10.53%, as shown in Figure 9.

Figure 8. App-switching behavior paths in the “Search → Search” pattern.

In addition, after the app-switching in this pattern, tools apps were chiefly used, followed by shopping and social apps. In addition, all app-switching behaviors with education apps were transferred to social apps.

Unlike Figure 4, this pattern shows that a user has submitted a query in both apps. It can be seen from Figure 8 that when a user searches again, it is easy to select apps of the same type. In addition, when a user’s first search occurs on a shopping app, they are likely to use other apps to search, such as social and local apps, rather than just shopping apps.
4.4.3. App-Switching Behavior Paths in the “Search → App Usage” Pattern

In the “Search → App Usage” pattern, the participants’ app-switching paths between different app types were more diversified. The participants had the most app-switching behaviors, and the app types used before and after the app-switching were the most.

As shown in Figure 10, when participants used video, communication, book, music, and audio apps, they would mainly switch to tool apps. Many app-switching behaviors led to switches to communication, social, shopping, video, and finance apps when the participants used tool apps.
Figure 10. App-switching behavior paths in the “Search &gt; App Usage” pattern.

In this behavior pattern, most app-switching behaviors occurred between tool and communication apps (19.91%). The second was between two different apps that belonged to tool apps. In the “Search &gt; App Usage” behavior pattern, participants preferred to use other apps of the same type when using tool apps.

More app-switching behaviors led to switches to communication apps, of which QQ and WeChat accounted for the most, similar to Figure 9. This reflects a strong correlation between users’ app-switching behaviors in mobile searches and social chatting behaviors.

In this pattern, users used more apps and switching paths were more complex. Although tools, social, and communication apps accounted for a large proportion, there was still much app-switching between the different apps.

5. Conclusions and Future Scope

Through a long-term user experiment in a real scene, this paper collected users’ smartphone interaction log data during the experiment and studied the app-switching behavior paths and patterns in users’ mobile searches. Firstly, this paper analyzed the basic characteristics of users’ mobile search processes. Furthermore, this paper studied...
the app-switching behavior paths in mobile searches from the perspective of switching probabilities between apps. This paper focused on the app-switching behaviors between different app categories.

In addition, this paper also identified users’ different behaviors in mobile search sessions, such as search, input, and app usage. Then, this paper proposed app-switching behavior patterns in mobile search sessions. These behavior patterns are a summary of user behavior changes in mobile searches.

This paper focused on the interaction characteristics of the app-switching under the three patterns of “Search → Search”, “Search → Input” and “Search → App Usage”. Finally, this paper combined the app-switching behavior paths and patterns, focusing on the user’s app-switching behavior paths under the above three patterns. It was found that there were obvious differences in users’ app-switching behavior paths under different patterns.

Our current research focuses on the essential characteristics and patterns of app-switching behaviors, which is also the focus of the human–computer interaction field. At the same time, some scholars have begun to focus on the dark side of app-switching behaviors. In terms of information security, past research [54] has found that some app switching is triggered by untrusted third-party apps, which can bring a bad experience to users. Tu et al. [55] were also concerned that user-installed apps may help unscrupulous individuals find specific users. In analyzing a city-scale anonymized dataset on mobile app traffic, they found that the set of apps was highly unique, and 88% of users with more than ten apps were uniquely re-identified by four random apps. As the environment of people’s interactions changes, people may switch between apps on different devices, such as smartphones, smart watches, cars, etc., which may raise concerns about privacy and security issues. Thus, it is essential to detect abnormal activities on apps, especially private information on some health apps. Wang et al. [56] developed a low-overhead and non-obtrusive mobile auditing framework, called mAuditor, that specifically monitors using a real-time onboard sensor and the network bandwidth usage of mHealth apps.

As for the implication, different mobile app developers can increase cooperation, obtained through the information flow, and achieve mutual benefit and win-win results. Through this study, users’ app-switching paths had a certain degree of focus, and so these mobile app developers with solid associations can achieve cross-platform access to information by sharing data streams. Mobile app developers can attract more potential users through cross-app business cooperation. Simultaneously, we can use the relatively mature Html 5 technology to help users quickly obtain information from different platforms in integrated web pages.

Of course, this paper also has some limitations. This paper is an empirical study. Although the research data are from the daily life of real users, there are deficiencies in the theoretical research. In particular, it failed to combine participants’ interview contents with this study. In addition, due to the requirements of participants and the consideration for privacy protection, the experimental data cannot be disclosed to researchers in the academic community, which is unfortunate for researchers in this field.

In the future, we will refer to the existing information-seeking behavior theory to propose an app-switching behavior theoretical model in mobile searches. The model will provide academic support for follow-up research. Further, future research will combine the participants’ interview contents after the experiment with log data to explore the in-depth intentions behind users’ behaviors. It can also realize the combination of quantitative and qualitative analysis. We think it will be a good supplement to help explain more complex user search behaviors.

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