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In-Depth Understanding of the Life Cycle of Users' Search Behaviour and Their Cognitive Journey When Installing Apps

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ABSTRACT

Understanding what motivates people to download apps is essential, as it influences the benefits these technologies offer and helps users find apps that fit their needs. By gaining better insights into user behaviour, we can enhance devices, services, and applications. Earlier work showed that the depth of available information influences the time and cognitive effort people spend searching for information to make an informed decision. When a user begins a search, they do not weigh all information equally. They rely on specific "entry point" cues to serve as a gateway. If an app fails these initial checks, the user will not expend the cognitive effort to look any further. In this work, we conducted an observational lab study and semi-structured interviews to investigate the cognitive heuristics and sequential behavioural pathways users employ when navigating app store environments, the importance of information cues presented by app stores, and the relationship between them across the app store stages. Using data mining approaches and path analysis, combined with theoretical frameworks of users' search behaviour, our research mapped the entire lifecycle of a user's app search and their cognitive journey from the moment they hit "search" to the final installation (e.g., Pre-Click to Post-Click).

Keywords: HCI theories and methods, Users' search behaviour, Laboratory experiment, Apps, Information cues, Decision-making, Heuristics, Data mining

INTRODUCTION

"Smartphones are the most personal devices people own and carry around with them all day" (Xu *et al.*, 2016, p. 244). Before viewing and downloading apps, consumers primarily rely on information cues provided by app developers, who create the app content and communicate what the app offers (Feng *et al.*, 2019; Alhejaili and Blustein, 2023a). Understanding what motivates people to download apps is vital, as it affects the value and effectiveness of these technologies (Alhejaili Adel, Blustein, 2022).

Building upon our earlier research and preliminary analyses (Alhejaili and Blustein, 2022, 2023b), we posit that modern app marketplaces overwhelm users with options. To survive in this environment, users cannot systematically evaluate every detail. Instead, they use "shortcuts to reduce cognitive burden," relying on combinations of specific information cues, such as ratings, reviews, and screenshots, to make rapid judgments. As part of a

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larger research project on users' search behaviour in the app domain, we provide additional analysis.

This study maps the exact behavioural and cognitive pathways users follow when searching for and selecting apps and exposes the relationships between information cues across the various stages of the app store (Lim *et al.*, 2015). Using data mining approaches and path analysis, we analyzed 84 empirical user search sessions. The findings validate dual-process theories of search behaviour, demonstrating that users balance the "cost" of searching (time and cognitive effort) against the "benefit" of finding the perfect app. They either use heuristic processing (satisficing: finding an option that is "good enough") or systematic processing (maximizing: comparing all options). Our path analysis reveals a strict, linear chronological funnel of information cue processing: users utilize ratings and app logos as instant gateways, verification metrics like number of downloads and screenshots as mid-funnel validators, and written reviews as the final arbiter of choice. More importantly, users do not navigate app stores randomly. They are highly sophisticated actors who use sequential information cues (Logos → Screenshots → Reviews) to manage cognitive load, and they dynamically dial their mental effort up or down (from 48-second satisficing to 175-second maximizing) depending entirely on the app's category.

Background and Related Work

The information presented in this section provides an overview of app stores in general, briefly describes some of the information cues displayed in the Google Play Store, and sheds some light on their importance. We also provide a brief overview of some app-selection heuristics.

App Stores and the Importance of Information Cues

App stores serve as the main platforms for obtaining, downloading, and sharing applications. They act as gatekeepers, establishing the guidelines for app development, organization, and dissemination (Dieter *et al.*, 2019; Alhejaili and Blustein, 2025). Based on the app store, the information presented to users differs to some extent, which has a considerable impact on users (Helf and Hlavacs, 2016). Before downloading any application, users enter the app's search term in the app store's search bar (Alhejaili and Blustein, 2023b). In the Apple App Store, the user will be presented with two apps without scrolling; however, in the Google Play Store, a list of apps is presented to the user (up to eight apps). Still, the "navigability and interactivity" are likely to be similar in both stores (Burgers *et al.*, 2016, p. 2). For the Google Play Store as presented in the Supplementary Details section, the information cues available on the app store while scrolling through the app description page are spread through multiple levels (e.g., before selecting an app to view while scrolling through the app list in the search page, after selecting an app to view more information about the app).

In terms of information cues, app descriptions serve as an essential medium for developers to convey their apps to the users (Feng *et al.*, 2019; Lin and Chen, 2019). Furthermore, the app review cue is essential, as users' attention is drawn to others' opinions, which eventually influence their perceptions/impressions of what they see and encounter during the decision-making process (Sundar, Oeldorf-Hirsch and Xu, 2008; Alhejaili Adel, Blustein, 2022). Also, the app names "play a crucial role," since they are considered "one of the first pieces of information that users encounter in the app stores," which typically provide some hints about the app's functions (Tafesse, 2021, p. 4). In addition, the number of downloads is one of the vital information cues users consider when downloading apps (Strzelecki, 2020).

It is important to note that the visual appeal of app icons, logos, and screenshots affects users. "Poor selection of logos can evoke negative evaluations and damage corporate image" (Wang and Li, 2017, p. 3). In the context of app stores, app icons offer a "powerful opportunity to attract" users' "attention in highly competitive app stores" (Chen, Yu and Gao, 2021, p. 1). Also, they are vital because they convey the app's first impression to the user (Hou, Ho and others, 2013; Oscario and Luzar, 2016). A "well-designed app" that "does not have a beautiful and attractive icon may get buried in the sea" (Hou, Ho and others, 2013, p. 3). App icons have "the power to make a difference between" skipping the app, tapping it, and "finally downloading it" (Oscario and Luzar, 2016, p. 1). Moreover, app icons are essential cues because they are the face of the app and the first thing users see when browsing app search results. Furthermore, this is the first chance app developers may have to convince users to tap their apps to see what they offer (Oscario and Luzar, 2016). In terms of the brand, Melissa (Pol, 2015) reported that the "brand appears to be an anchor in the choice of apps," where "the respondents have a strong preference for apps that contain a well-known brand over apps that do not contain a brand, or contain an unknown (i.e., non-existent) brand" (Pol, 2015, p. 4).

Heuristics

Dogruel *et al.* (2015) outline five distinct decision-making styles for app selection based on three user behaviours: whether they scroll the selection page, whether they examine additional information on the app page, and whether they ultimately install the first app they view. Four of the decision-making styles are variants of the "Take the First" (TtF) heuristics, and the fifth heuristic is called "Pondering Alternatives" (PA).

Simon (1955) introduced the "bounded rationality" term that proposes that "humans do not consider all possible outcomes before deciding, due to lack of time as well as cognitive constraints; rather, they operate rationally within given boundaries" (Wirth *et al.*, 2007, p. 779).

Research Objectives

Research indicates that the depth of available information affects how much time and cognitive effort users invest in searching for information to make decisions (Hong, Thong and Tam, 2004; Lurie and Mason, 2007; Alhejaili and Blustein, 2023b, 2023a, 2025).

App selection platforms show users a list of apps based on the terms they search for. On the other hand, the details about the algorithms that determine app rankings in search results are not publicly available (Marshall, Dunstan and Bartik, 2019). Everything in the app store environment "does not have the same impact, and that what comes first will have most significance in shaping what customers think about what they encounter later" (Graves, 2010, p. 81). The elements (information cues) that reside in the environment will influence users' behaviour. It is essential to consider what users see while searching for apps in the app stores because the first cues they look at can prime the way they perceive everything afterward (Graves, 2010).

This research builds upon three critical pillars of digital consumer behaviour literature: information cues, app selection and the sophisticated information search behaviour of users. In terms of the information cues and app selection, prior literature has established that users reduce cognitive burden by relying on specific external signals (cues) such as brand recognition, ratings, and peer reviews. However, the chronological hierarchy and interaction between these specific cues remain under-explored. Also, in terms of the sophisticated information search behaviour, and grounded in dual-process (Chaiken and Trope, 1999) theory and Herbert Simon's (1955) concept of "Bounded Rationality," the current models suggest users balance the cost of searching against the benefit of a perfect choice. They employ either Heuristic Processing (Satisficing: finding an option that is "good enough") or Systematic Processing (Maximizing: extensively pondering alternatives).

This paper bridges the previous frameworks, utilizing quantitative data mining to map the cognitive heuristics and sequential behavioral pathways users employ when navigating app store environments.

Based on earlier work, our research aims to address the following questions:

- How does the app category (context) drives users' behaviour?
- How can we map users behaviour to the used cognitive heuristics?
- What is the importance of the time spent searching for apps in relation to the used heuristics?
- In what chronological order do users process information cues (e.g., ratings, reviews, screenshots), and what cues act as entry vs. exit nodes?
- How does "bounce" behaviour (returning to search results) quantitatively reflect the cognitive investment of Maximizing versus Satisficing?
- How can we interpret the app choice life cycle?
- Are there any information cues used by participants that are considered a starting point?
- How can we interpret the search behaviour of viewing more than an app?

METHOD

Participants

In this research, 26 students were selected from a Canadian university via e-mail lists as a convenience sample, with ages ranging from 18 to 40 years. Participants were required to be at least 18 years old and possess an Android smartphone. The participants were compensated with $10 for their involvement.

Procedure

Employing a multi-method approach (Creswell and Creswell, no date), we integrated an observational lab study with a qualitative think-aloud protocol, followed by semi-structured interviews to investigate users' behaviours while choosing apps to install (Alhejaili Adel, Blustein, 2022; Alhejaili and Blustein, 2023b). Participants took approximately 30 minutes to complete the study.

For the app selection tasks, participants were requested to assist a hypothetical friend in locating two specific apps for designated scenarios. The researcher provided two scenarios from five categories: Nutrition and health, Music, Twitter, Flight tracking, Scanning receipts, and Word games. The full study guide can be found in (Alhejaili and Blustein, 2022).

Measures

To map the app selection lifecycle, this study utilized a dataset of 84 recorded user sessions, tracking demographic details, application categories, time metrics, and the utilization of 17 distinct information cues. To guide our research, we prepared the data for analysis by adapting multiple measures and coding rules, and collected multiple variables from (Dogruel, Joeckel and Bowman, 2015; Alhejaili and Blustein, 2022, 2023b). Briefly, in total, 57% (N = 48) of participants took reviews into account, 43% (N = 36) examined ratings, 33% (N = 28) perused the complete app description, 32% (N = 27) paid attention to the app's screenshots, and 23% (N = 19) checked the number of downloads. However, the overall distribution of information cues and factors considered by the participants is detailed in (Alhejaili and Blustein, 2022). In addition, we used data mining approaches and path analysis techniques to analyse the collected data to model the exact chronological steps users take as a network of nodes and edges to calculate inbound/outbound cue traffic (Kantardzic, 2019).

RESULTS

First, we describe our data in general, including the type of app they choose (context) and how they approach app search tasks. Second, we provide a holistic overview of the results and uncover several layers of insight across the following aspects: cognitive load and time investment, the pre-click scanning phase, the role of "bouncing" (going back), the complete app choice lifecycle, and the sequence order of information cues.

Behavioural Shifts by App Category (Context)

Users completely change what information they look for depending on the type of app they are downloading. For the health apps, users are highly diligent. They rely heavily on reviews and also show the highest propensity in the dataset to check permissions and full app descriptions. Users do not take health apps lightly and do a deep read before downloading. For the Flight/Travel Apps, users are highly focused on consensus. 64% of participants check reviews, and they heavily lean on screenshots to verify the UI/UX of the flight booking process. For the scanner apps, users care less about reading the full description and more about download numbers and ratings. This indicates they want a fast, proven tool without doing a deep dive.

Cognitive Load & Time Investment & Heuristics

As shown in Table 1 below, our dataset tracks the specific mental shortcuts (heuristics) users apply. By cross-referencing the applied heuristic with the total time spent installing an app, we observe a reflection of cognitive load. It also tracks this dual processing through applied cognitive heuristics, perfectly mapping the theoretical "cost of search" to the actual time spent.

Table 1: Mapping of the theoretical "cost of search" to the cognitive strategy of heuristics with some interpretations.

Cognitive Strategy (Heuristic)	Processing Type	Average Time Spent	Behavioural Profile in Data
Pure Take the First (PTtF)	Heuristic / satisficing	~48 to 56 seconds	The user does a rapid visual scan and downloads the first reasonable option without comparing.
Confirm, Take the First (CTtF)	Bounded rationality	~91 to 103 seconds	The user finds an app quickly but spends an extra 45 seconds confirming their bias (usually by checking the rating or a single review) before downloading.
Inform, Confirm, Take the First (ICTtF)	Bounded rationality	~135 seconds	A structured approach where the user reads a description and verifies it, but still ignores competing apps.
Pondering Alternatives (PA)	Systematic / maximizing	~168 to 175 seconds	The "Maximizers". These users refuse to settle. They actively switch between apps, read long-form reviews, and compare feature sets.

The Pre-Click Scanning Phase (The 40-Second Window)

One of the most striking findings is the time spent before first app was selected. On average, users spend 40.1 seconds just looking at the search results screen before they click on a single app. Users do not blindly click the #1 search result. They spend nearly a minute scrolling through the list. We know that during this 40-second window, users are heavily evaluating the app logo, the rating, and the app name/brand to decide which app is worth a click. This represents the baseline "search cost" every user pays to orient themselves in the store.

The Role of "Bouncing" (Going Back)

Our research tracks whether a user clicks "Go Back" after viewing an app's description page, as shown in Table 2. This metric perfectly validates the Cognitive Heuristics (PA vs. TtF) established on earlier analyses. Notably, the time spent on the search screen before the first click (~38 seconds) is identical for both groups. The time divergence occurs entirely on the app description page.

Table 2: The interpretation of whether users bounce back to search results.

Behaviour Type	Total Time Spent	Apps Viewed	Link to Previous Theory
No bounce (direct selection)	103.5 seconds	1.7 apps	This maps perfectly to the "Take the First" (TtF) satisficing heuristics. The user clicks an app, confirms their bias, and downloads it without returning to the search page.
Bounced (went back)	163.0 seconds	2.3 apps	This maps directly to the "Pondering Alternatives" (PA) maximizing heuristic. The user clicks an app, evaluates it, rejects it, goes back, and searches again.

The Complete App Choice Lifecycle & The Sequence Order

Our research mapped the empirical journey of the modern app-store user. The path analysis revealed a highly structured chronological order to app evaluation. We looked at the cues used as a starting point and the relationships between them across different stages of the app stores.

Regarding the relationship between cues, we found that it is not random. It is highly sequential and hierarchical. Users move from low-effort/quantitative cues on the search page to high-effort/qualitative cues on the app description page.

In terms of the starting point, "the hooks" and the entry point are when a user begins a search; they do not weigh all information equally. They rely on specific "entry point" cues to serve as gateways. If an app fails these initial checks, the user will not expend the cognitive effort to look any further.

The pre-click phase is where users spend 40 seconds scrolling the results and using the app logo and brand name to filter options. Then, the funnel trigger checks if the logo looks good; if it does, they click the app. Once on the page, during the post-click phase, users follow a strict visual sequence: [logo -> screenshots -> written reviews]. After that, the final phase is where the ultimate decision rests on social proof. Regardless of context or time spent, written reviews and ratings serve as the final checkpoints before installation.

Inbound/Outbound Nodes (Edge Traffic)

By mapping the transitions as a directed graph, we can see exactly which information cues act as "traffic drivers" (high out-degree) versus "final destinations" (high in-degree). App reviews are the ultimate destination for users. This node has the highest incoming traffic (29 inbound edges) but much lower outgoing traffic (17 outbound edges), which means that once users check the reviews, they rarely move on to other things; it serves as the final validation step. The app ratings are the grand central station for users. This node is considered the busiest intersection in the dataset. It has 26 outbound edges and 17 inbound edges. Users frequently check ratings and then immediately branch out to other cues. In terms of the brand/name, it is considered a top-of-funnel driver because this node drives significant traffic (19 outbound edges) and acts as a primary catalyst that sends users to explore other metrics. Lastly, users considered the app logo to be the dead-end node. Interestingly, the logo has 10 inbound edges but only 3 outbound edges. When users look at the logo late in their journey, it often serves as a quick final visual confirmation rather than a pathway to more information.

DISCUSSION

In this section, we explore some of our interpretations of the presented findings. When users are looking at the list of apps in the app store, the visual appeal of app icons, as an example, "can be assessed within 50 milliseconds, suggesting that web designers have about 50 milliseconds to make a good first impression" (Lindgaard *et al.*, 2006, p. 115). "Every piece of information in the app store matters and affects users. It has the power to make a difference between skipping the app or tapping on it and finally downloading it" (Oscario and Luzar, 2016, p. 1). This shows that app developers need to pay attention to app quality by considering the information cues they incorporate into their app design, because humans' choices are influenced by how information is presented and framed (Tversky and Kahneman, 1981). The modern app consumer is not a passive browser but a highly sophisticated information forager (Alhejaili and Blustein, 2023b).

Limitations

Studies on information-seeking behaviour and decision-making theories do not align on the types of search activities users engage in. This may stem from users' unpredictable behaviour when searching for apps, as various environmental factors can influence their scrolling habits (Allam *et al.,* 2019). Therefore, we cannot determine the type of decision-making or strategy followed. To some extent, we are trying to present our perspectives and interpretations of how users search for apps.

Future Work and Conclusion

While this study maps the explicit selection of cues, future research should integrate varying app stores (e.g., Apple App Store vs. Google Play Store) to determine whether differing UI architectures inherently alter the sequence of the information funnel.

This work investigated users' mental shortcuts and behaviours while browsing app stores through an observational lab study and semi-structured interviews. It focused on the significance of information cues across the app store search experience. The selection of these cognitive strategies is highly dynamic, dictated by the app category. By employing data mining methods and path analysis, our research mapped out the complete process of a user's app search journey, from initial search (Pre-Click) to installation (Post-Click).

In conclusion, our research provides a comprehensive, empirical framework of the sophisticated, bounded rationality exhibited by the modern app store consumer.

SUPPLEMENTARY DETAILS

The information cues available on the Google Play Store can be found in the online version, at https://drive.google.com/file/d/1CvqSE5RO-dtUFUGD0RoduHKl-Zfz1ipf/view

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