# Search Mindsets

## Understanding Focused and Non-Focused Information Seeking in Music Search

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## ABSTRACT

Music listening is a commonplace activity that has transformed as users engage with online streaming platforms. When presented with anytime, anywhere access to a vast catalog of music, users face challenges in searching for what they want to hear. We propose that users who engage in domain-specific search (e.g., music search) have different information-seeking needs than in general search. Using a mixed-method approach that combines a large-scale user survey with behavior data analyses, we describe the construct of search mindset on a leading online streaming music platform and then investigate two types of search mindsets: focused, where a user is looking for one thing in particular, and non-focused, where a user is open to different results. Our results reveal that searches in the music domain are more likely to be focused than non-focused. In addition, users' behavior (e.g., clicks, streams, querying, etc.) on a music search system is influenced by their search mindset. Finally, we propose design implications for music search systems to best support their users.

## CCS CONCEPTS

• **Information systems → Users and interactive retrieval**.

## KEYWORDS

music search, information need, mixed methods

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## 1 INTRODUCTION

Music listening has long been recognized as an important part of everyday life. As proposed by Merriam in 1964, *"... There is probably no other human cultural activity which is so all-pervasive and which reaches into, shapes and often controls so much of human behavior"*[32]. Over the past few decades, there has been a shift in how people access and consume music. Advances in technologies have enabled listeners to move from physical storage devices (e.g., cassettes or CDs) to digital storage through computers or mobile devices. Currently, supported by online music streaming services and platforms (e.g., Apple, Spotify), music consumption is even more pervasive than ever before – people can access millions of songs almost anywhere at anytime through a variety of modalities[39].

However, the ability to access vast amounts of music can contribute to information overload for users. While an abundance of content is available for consumption, only a small amount is actually relevant to users and their desired listening goals. Although music streaming platforms provide strategies to guide and recommend users to discover relevant music through personalization[12, 31], search remains an important way for users to find music.

Prior research in general web search categorized search activities into two broad categories: lookup and exploratory[30]. Lookup searches have well-defined information needs in the searcher's mind, whereas exploratory searches usually involve an open-ended, persistent and multi-faceted information seeking problem[48]. In addition, researchers have observed that lookup searches can be different than exploratory searches in terms of users' search activities, behaviors and strategies[1]. Because the user's information needs and goals can differ on whether or not that search is exploratory, search systems that fulfill lookup searches well may not perform as well when users want to engage in exploratory search[48].

However, we have little knowledge on whether this holds true for searches within the music domain since information needs for music listeners are specific and can be different than general web searchers. The most common reason of seeking music was to "listen for entertainment[25]". In addition, people who consume music are driven by their emotional, social, and cognitive needs[16], which suggests that user goals in music search may be driven by broader needs than those described by [6] and [40]. In a recent qualitative study of music search on an online music streaming platform, researchers identified the existence of distinct music search **mindsets** – focused, open and exploratory[17]. Results suggested that users searching with a focused mindset had a particular item in mind. In an open mindset, users had a seed of an idea in mind while searching. The exploratory mindset described users who employed search to learn more deeply about music.

In this mixed-method study, our goal is to characterize and distinguish between focused mindsets and non-focused mindsets to validate the findings from prior qualitative research[11] and identify associated behavior patterns at a large scale. We choose to collapse mindsets into two categories as users could distinguish actions and behaviors for focused mindset searches clearly [11]. First, we design a pop-up survey to collect users' mindset in real-time when they approach a music search. To further observe how mindset influences search behavior, we analyzed the surveyed users' behavior as they continued to use the platform. Specifically, our study answers the following three research questions:

**RQ1:** How does music search mindset vary among users?
**RQ2:** How does users' search behavior differ between mindsets?
**RQ3:** Can we infer users' mindset based on their behavioral signals when they interact with the music streaming platform?

Our research extends the previous literature in the general search domain and provides a novel contribution by studying the music search mindset. We found that music search mindset can depend on users' music preference and influence user behavior and activities in variety of ways. These behavioral signals can then be used to infer the search mindset. Altogether, our study provides insights for music as well as other content discovery and consumption services to best support their users when they approach a search.

## 2 RELATED WORK

**Categorization of general search activities.** Research in general web search have put considerable effort into understanding and characterizing the needs and goals of users. Search activity has been categorized as navigational (e.g., finding the URL of a desired web page) , informational (e.g., learning something from a web search) and transactional (e.g., performing a desired activity) [6, 40]. Beyond user goals, search behavior is influenced by factors such as the perceived task complexity and knowledge of the user[2, 27–29]. Liu et al.[29] found that web search behaviors, such as task completion time, number of different search engines used, and queries issued are all affected by the complexity and the preciseness of the search goal. Aula et al.[2] found that when tasks become more difficult, users issued numerous search queries, viewed many results, and spent more time on search result pages. Because these goals are meant to characterize general web search, they are broader in nature and describe user motivations that may not be consistent with how music listeners approach search.

**Examples of domain-specific search.** Music search is a type of a domain-specific search where user goals and needs may differ from general web search. Bainbridge et al. [3] found that users express their music needs in variety ways, ranging from bibliographic queries, genre and lyrics. Laplante and Downie [24] distinguish between hedonic and utilitarian outcomes in music information seeking. For utilitarian outcomes, users are looking for something to listen to or hoping to gain information about music.

Another example of domain-specific search is product search. Although product search has similar search categories as web search (browsing vs. directed search)[41], the shoppers' decision-making process is different[26]. Recent studies focus on using behavioral data to improve the search experience to better align with shoppers' needs. Wu et al.[49] used implicit feedback to identify two stages of searching: comparing search result pages and deciding to purchase on description pages. Researchers from Pinterest have revealed that goal specificity (e.g., visiting a web site for a specific goal) and temporal range (e.g., when the user envisions the goal will be achieved) influence user intent[10]. Su et al. [47] determined three types of product search intents in a commercial product search engine that also range in specificity and focus.

Prior work in describing information needs in product search suggests that there is a value in differentiating between general web search and more targeted domain-specific search, such as music. In this paper, we describe the particular information seeking behavior of music listeners when they either have something specific they want to consume, or they are more open to suggestion.

**The role of music in society.** Scholars from various disciplines have long studied the origin and purposes of music and why people listen to music. In general, scholars agree on the fundamental function that music provides for humans – to produce pleasure[46] and pass the time[18]. One line of research focuses on the broad impact of music on culture and society, referring music as a medium with multiple social and cultural benefits[4, 18, 32, 33, 36]. Other studies focus on the ways in which people use music in their everyday lives [43–45].

**User characteristics influencing music consumption.** Research has suggested that the behavior of people interacting with music can be shaped by listener's individual differences such as age[9, 34], gender[5, 9, 23, 34], culture [37], personality traits[8, 9, 13], and musical preferences [15, 42–44]. Studies also demonstrate that music listening is context-dependent and influenced by the situations (e.g., where and when). Researchers have observed that music listening predominantly occurs at home, while driving, or while using public transport [14, 22, 35]. Krause et al. [22] found that the intensity of the consequences of music listening varies across listening locations. The time of day or the day of the week when music listening occurs is also important – music is more likely to help people concentrate during the workday (8:00 a.m. – 4:59 p.m.) than during the evening (5:00 – 11:00 p.m.)[35, 38].

In sum, as music serves different functions for society and individuals, our study intends to extend prior work on general web search to examine search in the music domain.

## 3 RESEARCH PLATFORM

We conduct our study on Spotify, a widely used music streaming platform available on mobile devices. Search is a prominent feature on this platform and it requires users to type into a search bar located at the top of the screen. Currently, the feature relies on an instant search system, which updates the search engine results page (SERP) with each keystroke. The SERP itself features a single top result displayed prominently at the top. For some artist or genre searches, the SERP features a carousel of relevant playlists that users can scroll through horizontally underneath the top result. Other relevant results follow, clustered according to entity type in the following order: songs, artists, podcasts, albums, playlists, podcast

**Table 1: Feature definitions**

| | | |
|---|---|---|
| ***User features*** | | |
| Demographics | Gender/Age | User's self report gender (female or male) and age |
| Engagement | Account age<br>Days active | The total days as a user of the platform<br>The total days active |
| Music Preference | Music discovery rate | The percentage of novel tracks listened to by the user in the past month. |
| ***Session features*** | | |
| Session context | Time of the day<br>Weekend | Day parts include: early morning, morning, noon, afternoon, evening, night<br>Weekdays or weekends (Saturday and Sunday) |
| Session length | Session duration | Time duration from start until the end of the focal session (in seconds) |
| Session switching activities | Number of switching activities | Number of times the user switches between behavior types (e.g., keystrokes, clicks, streams, etc.) |
| ***Activity features*** | | |
| Query | Query edit distance<br>Final query length<br>Query keystroke shape | Max edit distance [20] of the queries issued in the focal session.<br>Number of characters of the final query issued in the focal user session.<br>Query shapes (D, B, L, and Γ patterns) [7] for all search queries issued in the focal user session. |
| Searching | Search duration<br>Number of searches<br>Number of addition/deletion | Time spent engaging in search activity (in seconds)<br>Number of searches conducted within the focal session<br>Number of characters typed/deleted |
| Clicking and Streaming | Time to first click<br>Rank of the first/last click<br>Entity type of the first/last click<br>Music stream | Time (in seconds) spent from the start of the session to the first click<br>Rank position of the first/last click<br>Entity type: playlist, track, album, artist, and others<br>Whether the current user session includes a music stream longer than 30 seconds |

episodes, and user profiles. In addition, users are able to click on a context menu for each song result, where they can take actions such as saving the song, adding to playlist, sharing, or viewing the album/artist.

# 4 SURVEY DESIGN AND DATA COLLECTION

## 4.1 Survey Design and Usability Test

Our survey design is guided by usability tests. We ran the tests with 10 users (4 internal employees and 6 external participants) to ensure that we understood a) whether our survey was able to capture respondents' mindset with fidelity; b) how respondents would interpret and answer the questions; c) how the survey triggering process could possibly impact users' subsequent experience. To qualify for the usability study, participants needed to be Android mobile phone users and had to have searched on Spotify at least 3 times in the week before our study. Participants ranged in age from 21 to 39, and included six females and four males. External participants in the usability study received a $50 gift card.

We conducted face-to-face, 30 minute usability tests combined with semi-structured interviews with each of the participants. The entire study included three phases: warm-up, search tasks, and post-interview. We began the study with a warm-up phase by discussing participants' music taste and habits in general and then narrowed the conversation to focus on search in the platform. In the search tasks phase, participants were asked to recall their most recent searches under three different scenarios: a general search (any recent search), a non-focused mindset search (open-ended music needs), and a focused mindset search (specific music needs). For each scenario, we asked participants to provide details and walk us through their search process using an Android mobile phone that we provided. The survey was triggered when participants navigated to the search page. During each task, we observed participants' reaction and recorded their responses. We followed up by asking the questions "What do the survey question/response options mean to you?" and "How did you decide your answer?' After completing the tests, we concluded the study with a brief interview to understand the participants' overall experience with the survey and the triggering process. We wanted to ensure that surveying the user's mindset was reasonable, and the process was not overly disruptive nor changed user's subsequent experience.

We designed the survey to have only one multiple-choice question because we wanted to minimize the interruption of the pop-up survey and allow users to continue their desired behavior as quickly as possible. The survey question and the response options intended to capture the current mindset of users while searching. We tested different versions of the survey question and response options, and we updated the design based on the results of the usability test.

After several rounds of feedback, the final survey design included the question: "Do you know what exactly you want to find?" Response options included *"Yes. I am looking for one thing"* to capture the users' **focused** mindset, and *"No. I am open to suggestions"* to capture the users' **non-focused** mindset. Users could also opt-out from the survey at anytime by clicking the "DISMISS" button. Based on our usability tests, this version best captured the users' search mindset. For this final version, study participants reported that the survey question and selections are "clear and answerable." In addition, they reported that the final version would not change their subsequent experiences in using the platform. In terms of the triggering process, users reported that the "it would be annoying if this happens on my phone every time...one time would be OK though." We therefore decided that the survey would only be triggered once in a user's lifetime on the platform.

We sent out the surveys in three waves to 50,000 Android users in the United States during the month of July 2018. To qualify for the survey, users had to have searched at least 3 times on Spotify in the week before we sent out the survey. We chose this cutoff to make sure that users had encountered the search feature prior to receiving the survey. To minimize the coverage bias, we used random sampling and controlled for the product type – free users and subscription users were equally likely to receive the survey.

## 4.2 Survey Responses and Observational Data

**User Session.** The second component of our methodology captured users' behavioral data when they interact with the search platform. As users interact with the search platform, the system records a constant stream of search event logs. User sessions are then segmented: each user session begins with a keystroke where the user types something in the search bar, and it ends if the user is idle for more than 10 minutes[19]. We summarize each user session using three general sets of features to describe: the users who conduct a search, the search session and its context, and the user activities in the session. Informed by the prior research in Section 2, we construct the three categories of features for each user session: user features, session features and activity features (see Table 1).

**Survey Responses and User Sessions.** The survey remained live for two weeks for data collection during the month of July 2018. In the end, 16% of the surveyed users triggered the survey, and 27% of them responded the survey. In total, 2,234 users responded to the survey and generated 27,504 user sessions within the two weeks.

To understand how the users' behavior is associated with different search mindsets, we focus on the search activities in the *first user session* immediately following the survey response time. As some users responded to the survey without searching for anything within 10 minutes, we excluded those user responses. In total, we had 1,779 survey responses that we were able to associate with a user session. We refer this set of session data for 1,779 unique users as the *labeled dataset*. The median time interval from the survey response time to the start of the first search activity is 3.6 seconds. We refer to the rest of 25,725 user sessions without a mindset label as the *unlabeled dataset*. User search sessions have a median time duration of 23.7 seconds and the median number of searches is two.

# 5 ANALYSES AND RESULTS

In this section, we address our three research questions. We used the *labeled dataset* to discover the patterns associated with the different music search mindsets and then utilized the *unlabeled dataset* to validate those patterns at scale. To answer RQ3, we built a supervised machine learning model based on the features in Section 4.2.

**RQ1: Music searches are more likely to be focused, and the search mindsets depend on user's personal music preference.**

From the survey responses, we observed that music search mindsets vary across users. Our data indicated that users are more likely to have a focused mindset when they approach a search: 65% of the survey responses indicated focused searches. In addition, we performed a regression analysis to assess the main effects of the user features described in Table 1 to their search mindsets. The regression analysis was conducted with each user session as the unit of analysis with the search mindset as a binary dependent variable and user features as independent variables. Overall, there is a significant effect of user's *Music Discovery Rate* (Wald $\chi^2$=4.039, df=1. Sig.<.05). Users who discovered more novel music tracks within the past month are associated with an increased likelihood ($\beta$ = 0.635) to search with a non-focused mindset. We found no significant effects of user gender, account age, and days active on the search mindset.

**RQ2: Users' searching, clicking and streaming behavior differ between focused vs. non-focused mindsets.**

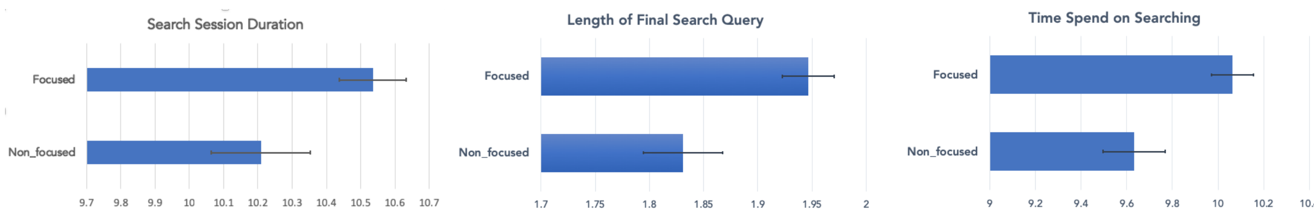
**Sessions.** Our second analysis focused on assessing each mindset's relationship to the search session features in terms of the session context, the duration and the number of switching activities. We conducted a regression analysis with the search mindset as a binary dependent variable and session features as independent variables. The analysis was conducted with each user session as the unit of analysis nested within the user gender, to account for the non-independence of sessions among users with the same gender. We include other user features (i.e. user age, account age, active, discovery rate) in the model as control variables. The results demonstrate a significant association between the session duration and mindset (Wald $\chi^2$=4.049, df=1. Sig.<.05): search sessions with the focused mindset tend to last longer ($\beta$ = 0.037) than the search sessions with the non-focused mindset (Figure 1a). There exists no significant effects of the search context on the mindsets: user search mindset does not vary by time of day or day of week.

**Activities.** To evaluate if user activities differ between search mindsets, we conducted three regression analyses to assess the relationships between search mindset and queries, search behavior, and clicking and streaming activities. These analyses were conducted separately to avoid the effect of multicollinearity. All the regression analyses modeled search mindset as a binary dependent variable, and each analysis included the query features, searching features, and clicking/streaming features separately as independent variables. The analyses have each user session as the unit of analysis nested within the user gender and session context, to account for the non-independence of sessions among users with the same gender and searching at the same time. We included other user and session features as control variables.

*Query:* We found that there are significant associations between search mindset and querying behavior. Features including query length (Wald $\chi^2$=3.885, df=1. Sig.<.05) and keystroke patterns (Wald $\chi^2$= 4.850, df=3. Sig.<.05) have significant effects. Specifically, users search with focused mindset tend to issue longer queries using more characters ($\beta$ = 0.151) than the queries issued by non-focused mindset search (Figure 1b). In addition, users searching with focused mindset are less likely to issue D-shape[7] queries ($\beta$ = -0.132) compared to non-focused mindset.

*Searching:* Users' search activities in terms of the search duration (Wald $\chi^2$= 9.507, df=1. Sig.<.01) and the total number of characters the user typed (Wald $\chi^2$= 6.888, df=1. Sig.<.01) significantly differ between search mindsets. Specifically, users who search with a focused mindset tend to spend a longer time while searching ($\beta$ = 0.171) and have more total number of characters added ($\beta$ = 0.148) than those users with a non-focused mindset. Figure 1c illustrates the estimated mean of time spent for search under each mindset.

*Clicking:* Users' clicking behaviors, such as time to the first click (Wald $\chi^2$= 4.677, df=1. Sig.<.05), rank of the first click (Wald $\chi^2$= 11.842, df=1. Sig.<.001), entity type of the first click (Wald $\chi^2$= 15.211, df=4. Sig.<.01) and last click (Wald $\chi^2$= 16.649, df=4. Sig.<.001), differ significantly between search mindsets. Users searching with a focused mindset tend to spend more time before their first click ($\beta$ = 0.023). The first clicked entity by users with a focused mindset tend to have larger rank positions ($\beta$ = .141), which suggest that they tend to scroll down and click on a lower ranked entity. In




**(a) Mean of session duration (in seconds) for focused searches vs. non-focused searches**

**(b) Mean of final search query length issued by focused vs. non-focused searches**

**(c) Mean of time (in seconds) spent on search for focused vs. non-focused searches**

**Figure 1: RQ2: Users' behavior differs between mindsets**

terms of their clicked entity type, we observed that the non-focused mindset searchers are more likely to click on a playlist compared with other types of entities such as tracks, albums, or artists. A playlist can be generated by editors based on certain topics or popularity, by algorithms based on the personalized recommendation, or even by other users. Therefore, it may contain a more diverse set of musics favored by the users who search with a non-focused mindset.

*Streaming:* We found that focused mindset search sessions are less likely to involve a music streaming (Wald $\chi^2$= 3.165, df=1. Sig.=.075, $\beta$ = -0.045) directly after a search, but they are more likely to have clicks on the Context Menu button (Wald $\chi^2$= 3.223, df=1. Sig.=.073, $\beta$ = 0.093) – this button is one step before users saving search results to their personal music repository. However, the two observations are marginally significant with small effect sizes.

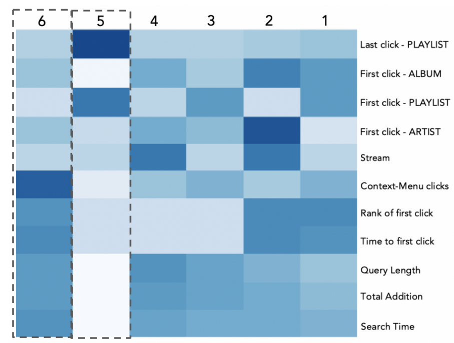



**Figure 2: Clustering heatmap: 5 & 6 represent the non-focused and focused mindset session cluster respectively**

**Unsupervised clustering validates the patterns at scale.** So far, we have identified a set of behavior patterns using the labeled dataset. Next, we validate the patterns at scale based on the clustering analysis of the larger unlabeled dataset and interpreting each cluster. We ran K-means clustering, and used the "elbow test" to set the optimized number of clusters (k)[21].

We report the results of our clustering analysis in Figure 2. Figure 2 is a column-standardized heatmap of the cluster centers for six groups with respect to the features. We found that the clusters reflect the behavior patterns described in Section 5, which correspond to focused and non-focused search sessions. Specifically, the user sessions from cluster 6 have a longer search duration and time to first click. Users from this cluster had more keystrokes, issued long queries, scrolled down and clicked on the lower-ranked entities. They used the context-menu button frequently, but engaged less with music streaming and playlist clicks. We interpret this cluster as the "**focused mindset**." In contrast, the user sessions from cluster 5 had shorter search duration and time to first click. Users from these search sessions used fewer keystrokes and issued short queries, but they clicked on playlists more frequently. This cluster includes user sessions whose behavior patterns correspond closely to the patterns identified for the **non-focused mindset**.

Interestingly, the clustering results suggest that the search mindset may be related to user goals, which is consistent with the findings from the prior work about user goals[17]. User sessions from clusters 2 and 4 spent more time searching, querying and music streaming, suggesting that user goals in these clusters may be listening. However, these two clusters presented behaviors (e.g. time to first click, rank of clicked entities, clicked entity type) associated with different mindsets. User sessions from cluster 2 demonstrate the behavior patterns corresponding to a focused mindset – users engaged a longer time before the first click, clicked on lower ranked entities, and clicked on artists and albums frequently, whereas user sessions from cluster 4 follow the behavior patterns that we observed for the non-focused mindset.

**RQ3: Search mindset can be inferred from lower-level user behavioral signals.**

So far, we have described how music search mindset is associated with different behavior patterns. However, is it possible to use these behavioral signals to infer users' search mindset? Such information would be useful in adjusting the user interface and search results to better serve users based on their needs. In this section, we answer our third research question by building predictive models.

We utilized the features proposed in Section 4.2 and consider the following two prediction tasks: 1) how is the prediction power improved by adding behavior features chronologically throughout the session, and 2) after we have observed all the features within a session, can we predict whether the search mindset was focused or non-focused? As different features can be observed in chronological order during the user session, these two tasks can not only indicate how well we can infer the search mindset, but can also suggest how quickly we can infer search mindset. For example, user features and session context features are available before the start of a user

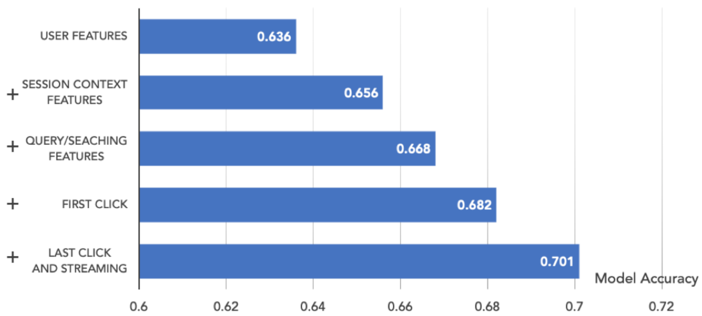



**Figure 3: Model performance improved by adding features**

session, but we can only obtain the clicking and streaming features at the end of the user session.

We implemented several supervised machine learning models to predict the search mindset for a user session using the labeled dataset as ground truth. As the dataset is unbalanced with majority user sessions having a focused mindset, a random guess would achieve classification accuracy of a 65% in predicting focused mindset. We trained our model by adding class weights to consider for the unbalanced data. We used logistic regression as a baseline model, and three separate models using bagging, boosting and random forest ensemble methods on a decision tree classifier to improve the model performance. We split the dataset to have 70% training data and 30% test data. We conducted a three-fold cross validation on the training data to find the optimized parameters for the model and applied the trained model into the test dataset. We report our model performance using accuracy, precision, recall, and F1 score.

Overall, our results demonstrate the potential to infer music search mindset based on our proposed user session features. Figure 3 demonstrates the improvement of the model predictive power by adding features based on the approximate chronological order that they can be observed throughout the user session. By including all the features, the model is able to predict the focused mindset with an accuracy rate of 70.1% (F1 = 0.806, Recall = 0.917, Precision = 0.718), a significant improvement of accuracy rate from both the random condition and the baseline model.But, when we only include the user and session context features in the model, the predictive power is quite low (65.6%) and the user's music discovery rate is still the most individually predictive feature. This result also indicates that it can be very challenging to predict search mindset at the session start. But the model's predictive power improves by including more user activities. Specifically, by adding features from search and query activities that occur in the early stage of a user session, the model performance improves to 66.8% accuracy. Eventually, by adding features extracted from users' clicking and streaming activities that occur in the late stage of a user session, the model performance achieves its best performance.

## 6 DISCUSSION AND CONCLUSION

Our results demonstrate that users' behaviors differ between search mindsets during search sessions. Specifically, users expend more effort while conducting **focused mindset** searches: they issue longer search queries, spend a longer time searching and a longer time to first click. In addition, they scroll further down the search result list and click on lower-ranked entities. They tend not to listen and stream these search results directly after the search, but are more willing to add the search results into their saved music library immediately after the search. Users searching with a **non-focused mindset** tend to put in less effort but rely more on the system for good search results and suggestions. For these users, their queries are shorter; they spend less time on searching and before their first click; but they are more willing to click on the very first entity the system returned, and those clicked entities are more likely to be a playlist. Finally, based on supervised machine learning techniques, we used these discovered behavioral patterns to recover a user's music search mindset in a user session.

These insights provide opportunities for content discovery and consumption services broadly (e.g., YouTube or Netflix) to develop strategies to better serve their users when they approach a search. Although it may be very challenging to infer search mindset at the very beginning of the search session, users' past music or content discovery preferences can provide a baseline estimation of what the search mindset for the current session is likely to be. As users' activities and behavior signals increase chronologically, the search system and interface can be adjusted at real-time to accommodate for the specific needs of distinct user mindsets. For focused mindset searches, the system should provide support that reduces users' searching and querying efforts, such as query auto-completion tools. To address non-focused mindset searches, the system can offer additional content recommendations, as these users rely more on the system for search results and music suggestions. For example, music streaming services can prioritize showing the playlists for non-focused mindset searches while showing the specific and targeted content (e.g., music track or album) for focused mindset searches.

Several limitations exist in the current study. First, the survey triggered only once per user's lifetime, so our labeled dataset includes only one session per user. As users' previous search sessions can also impact their current search session, we can potentially include that information when inferring searching mindset. Second, mindset may change over time. We partially mitigate this issue: we survey user mindset immediately before the beginning of the session and consider only the first user session, which tends to be relatively short with a median time duration of 23.7 seconds. Future studies can investigate whether and how the user's search mindset would change over time. Third, while we sought to present a broad overview of search behaviors and activities associated with two types of mindsets, our results from the clustering analysis suggest that user goals in searching music can also play a role. Future work can more deeply investigate the role of user goals as they differ across types of mindsets. Finally, as our data consists of Android users on one specific music streaming platform within one country over two weeks, future work can reproduce the current study by collecting more data with from a broader set of users across different content streaming systems for a longer time period to validate generalizability across platforms.

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