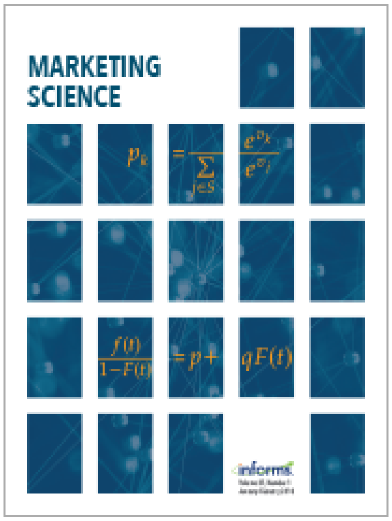

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Estimating Position and Social Influence Effects in Online Search

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Abstract. This paper contributes to the literature on structural modeling of online consumer search by incorporating both product position and social influence effects (e.g., product popularity) while allowing consumers to select multiple items per search and learn adaptively about their match with the platform. Disentangling the product position and popularity effects is challenging because they are typically highly correlated in field data. To address this, we leverage a publicly available data set from a field experiment conducted on an online music platform. The experimental design motivates a two-step estimation procedure to aid identification. We also introduce a content-based filtering method to predict individual download probability for all products, including those not sampled in the experiment. Combining this download decision model with our structural search model, we conduct counterfactual experiments that show (i) revealing product popularity and sorting products accordingly improves consumer efficiency by reducing search effort and increasing downloads; (ii) random sorting combined with product popularity disclosure stimulates more search activity, potentially boosting advertising revenue; and (iii) sorting based on personalized ranking with displayed product popularity enhances engagement by increasing both downloads and search efficiency.

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Keywords: multi-item selection in consumer search • product position • social influence • information disclosure • content-based filtering • generalized Weitzman model

1. Introduction

Consumers often need to choose among alternatives with which they have little or no prior experience, for example, books, songs, movies, TV shows, and hotels. When making their decisions, consumers may rely on information supplied by others, such as sales rankings and product ratings. This reliance on others' behaviors and opinions is known as social influence. In addition to social influence information, a product's position in a listing may also play an important role in consumer choice. For instance, consumers often read from top to bottom, leading them to notice and search for products listed near the top first. Different combinations of social information disclosure and product listing strategies could have profound implications on which products are more likely to be chosen by consumers. However, previous research on online search provides little guidance about how platforms should act. This is because the literature has considered only one of these two factors, but not both.[1]

To address this major shortcoming in the literature, our paper estimates the effects of social influence and product position on consumer search behavior. More specifically, we study product popularity as one form of social influence. Our ultimate goal is to provide more insights that can help platforms optimize their strategies about how to display products and disclose social information. Disentangling social influence and product position effects is challenging because they are usually highly correlated in field data, as platforms often sort products according to their popularity. To overcome this challenge, we utilize data from a field experimental study conducted by Salganik (2008). We argue that the experiments, together with our structural search model, allow us to separately identify these two effects on consumer search behavior.

In all experiments, participants can sample from 48 songs, each from a different band that is unknown to them, and download as many as they want in a single search session. Participants are randomly assigned to one of two conditions: (i) the Independent group, and (ii) the Social Influence group. In the Independent group, no popularity information (i.e., number of downloads by previous participants) is provided. In the Social Influence group, popularity information is disclosed to each participant. In these experiments, songs were presented to participants using one of two display formats: column or matrix. In the experiments with matrix format, songs are sorted randomly for participants in both the Independent and Social Influence groups. In the experiments that use column display format, songs are sorted randomly in the Independent group for each participant (see Figure A.8 in Web Appendix E); however, in the Social Influence group, songs are sorted by their popularity (see Figure A.9 in Web Appendix E).

These two conditions motivate us to implement a two-step estimation procedure to separately identify the effects of position and popularity on consumer search behavior. In the first step, we use the data from the Independent group to isolate the position effect on search behavior because the Independent condition ensures the absence of social influence. In the second step, we fix the position effect identified from the Independent group and use the data from the Social Influence group to identify the effect of product popularity on consumer search behavior.[2]

The previous literature on empirical search models always assumes consumers choose one item per search session. To capture the feature that participants can download multiple songs per search session (similar to Spotify, Bandcamp, etc.), our structural sequential search model incorporates a model developed by Olszewski and Weber (2015a, b). Their model is a generalization of the standard search model by Weitzman (1979), where consumers can only choose one item per search. In contrast, Olszewski and Weber (2015a, b)'s model allows for multiple items to be selected within a single session, thus relaxing this limitation. In addition, our search model allows consumers to adaptively learn about their match value with the platform. By combining adaptive learning, diminishing return in marginal utility, and increasing search cost in product position, we characterize the optimal selection and stopping rule, which allows us to estimate the search model.

In our model, we assume a consumer downloads a song if and only if they like it after sampling; moreover, by modeling consumers form adaptive beliefs (instead of rational expectation) about their match with the platform, we do not need to model the actual probability that they like a song in order to estimate our search model. However, to conduct counterfactual experiments, we need to predict each consumer's download probability for every song, including those not sampled in the original experiments. To achieve this, we train a dedicated machine learning model, a *content-based filtering recommender system*, and employ it to predict individualized download probabilities for each song. This method relies on multiple layers of neural networks and has the advantage of incorporating rich and unstructured song content and consumer heterogeneity.

By combining this predicted download probability model with our structural search model, we conduct four counterfactual experiments to examine the impact of different ways of arranging product position and disclosing social influence information for each display format (matrix versus column): (i) random assortment without popularity information, (ii) random assortment with popularity information, (iii) assortment based on popularity, and (iv) assortment based on a personalized recommender system with popularity information displayed. Our results suggest that platforms relying primarily on sale revenue should favor a column format that sorts songs by displayed popularity, as this format can increase consumer purchases. In contrast, platforms relying on advertising revenue may prefer the random assortment with popularity information displayed in the column format, as it generates higher consumer engagement (measured by the number of songs sampled); the extended search time increases opportunities for ad impression. Furthermore, platforms seeking to optimize efficiency and purchases may benefit from sorting based on a personalized recommender system, which customizes song ranking to individual preferences.

The rest of the paper is organized as follows. Section 2 reviews related work on consumer search and observational learning. Section 3 describes the data used for analysis and provides reduced-form evidence. In Section 4, we introduce our empirical sequential search model, which incorporates the generalized Weitzman framework by Olszewski and Weber (2015a, b) and adaptive learning. Section 5 discusses the estimation approach and identification. Section 6 presents the estimation results. Section 7 investigates the effect of different counterfactual designs on participants' search behavior and provides managerial insights. Finally, Section 8 concludes the paper.

2. Literature Review

Our paper is related to the literature on estimating product position effects in online search. Various methodological approaches have been employed to isolate the position effect, including latent instrumental variables (Rutz et al. 2012), simultaneous equations (Ghose et al. 2014), regression discontinuity (Narayanan and Kalyanam 2015), control function (De los Santos and Koulayev 2017), randomized ranking (Ursu 2018), and dynamic structural modeling with learning about content quality and match (Roos et al. 2020). However, none of these studies takes into account the effect of social influence on the search process. Social influence could be a significant factor affecting search behaviors and product rankings on online platforms. Although there is a large literature of social influence pioneered by Banerjee (1992) and Bikhchandani et al. (1992) (e.g., Çelen and Kariv 2004, Cai et al. 2009, Ching 2010, Zhang 2010, Tucker and Zhang 2011, Krumme et al. 2012, Zhang and Liu 2012, Newberry 2016, Carrera and Villas-Boas 2023), none of them incorporates product position effect or uses a search model framework. In this paper, we address this important gap by examining both product position and social influence effects in the context of online search, using a structural search model.

Our paper also contributes to the literature on structural search models based on Weitzman (1979). Early examples are Ratchford (1982), who provides an economic framework for studying consumer search and choice behavior, and Moorthy et al. (1997), who study the effect of consumers' prior beliefs on their search strategies. More recently, a number of empirical studies have also applied the framework of Weitzman (1979) to various search contexts. Prominent examples in this stream are Kim et al. (2010), who apply the model to clickstream data; Honka and Chintagunta (2017), who extend the model to study the purchase decisions of consumers; and Kim et al. (2017), who develop a probit model of sequential search to study aggregate demand for durable goods.[3]

Despite its merits and widespread application, Weitzman (1979) only applies to situations where consumers just choose one item in each search session, which renders it unsuitable for our data and some other real-world situations. Recently, Olszewski and Weber (2015a, b) extended the Weitzman model by allowing consumers to choose multiple products in a search session; they refer to their model as the generalized Weitzman model. We extend their framework to an estimable structural model to capture participants' behavior in our empirical context. Because this model does not have a closed-form solution, we estimate it using a logit-smoothed accept-reject simulator (AR simulator), which has been used in the estimation of related search models (e.g., Honka 2014, Honka and Chintagunta 2017, Ursu 2018).[4]

Our research makes use of the data from Salganik (2008), who designed and ran a field experiment to study the social influence in entertainment markets. This experiment provides unique detailed data containing the individual-level sampling and downloading behavior dynamics under control/treatment conditions. However, Salganik et al. (2006), Salganik and Watts (2008), and Salganik and Watts (2009) only used the data to measure the impact of social influence and different assortments of products on the average market shares of songs. They use the Gini index to illustrate that displaying products' popularity and sorting them based on it leads to greater inequality of success. Using the data from Salganik et al. (2006), Hendricks et al. (2012) model the effect of observational learning on the probability of herding for both high- and low-quality songs, and use the aggregated songs' download shares to test their model predictions in the long run. However, they do not account for how search behavior influences song selection, thereby missing the interplay between product position and social influence on participants' search behavior.

From a managerial perspective, platforms must decide whether and how to disclose social information. Research has focused on ranking and recommendation systems, showing that utility-based rankings, such as those examined by Ghose et al. (2014), Chen and Yao (2017), and De los Santos and Koulayev (2017), outperform traditional methods in revenue and engagement. Additionally, Ursu (2018) and Greminger (2021) provide insights into how utility-based rankings and position effects influence consumer behavior. More recently, Compiani et al. (2024) propose ranking rules that optimize both consumer surplus and platform revenues. In contrast to these studies, our results demonstrate that incorporating social influence into a structural search model offers distinct managerial insights—particularly on how product position and popularity signals jointly shape ranking strategies and drive consumer engagement.

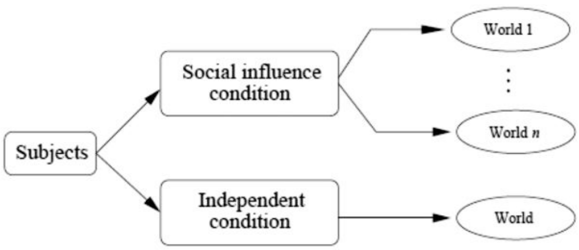
3. Data Description

Salganik (2008) created a website called MusicLab, where participants can sample and download any of the 48 songs available there. Our analysis makes use of three experiments conducted there. These three experiments have around 10,000 participants. The data collected from MusicLab are particularly well suited for our research objectives. It tracks participants' sampling and downloading decisions at the individual level on a platform that mimics commercial platforms such as Spotify, iTunes, SoundCloud, and Pandora (see figures in Web Appendix F).

3.1. Experimental Design

Three experiments were run at different times. Experiment 1 uses a matrix display format, where songs were arranged on the screen in a 16×3 matrix. Experiments 2 and 3 use a column display format, where songs were shown in a single column. In each experiment, participants arrived sequentially and were randomly assigned to one of the two groups, "Independent" or "Social Influence," as shown in Figure 1.[5] The Independent group participants only observed the names of the songs and the corresponding bands. The Social Influence group differs from the Independent group by

Figure 1. Experiment Design



disclosing past participants' choices, that is, the number of times each song has been downloaded, which we refer to as "popularity." Here, it captures the idea of social influence by providing an informative signal about the desirability of songs by others.[6]

It is important to note that in experiment 1 (matrix format), songs are *always* sorted randomly in both the Independent and Social Influence groups for each participant (see Figures A.6 and A.7 in the Web Appendix). In experiments 2 and 3 (column format), songs are also sorted randomly in the Independent group (see Figure A.8); however, in the Social Influence group, songs are sorted by their popularity (see Figure A.9).[7] The setup in experiments 2 and 3 closely mirrors real-world scenarios where product position and popularity are often confounded, creating challenges for researchers to disentangle these effects when analyzing search behavior data.

One advantage of this experimental design is that it had multiple parallel worlds of the Social Influence group, where each world had its own initial condition and evolved independently over time. This created multiple realizations of the same process and alleviated the sampling error problem when we estimated our model. Experiments 1 and 2 each have one Independent world and eight Social Influence worlds. Experiment 3 has one Independent world and two Social Influence worlds.

3.2. Experimental Procedure

Upon joining the experiment, each participant needed to complete a survey, which provided their demographic information and internet connection type. After the survey, participants were randomly assigned to one of the above groups and were directed to the screen where they could choose songs to sample. After sampling a song, the participants decided whether to download it or not. Then, they return to the main menu, and they can choose either to continue their search or exit the experiment (see Web Appendix E). It is important to highlight that participants cannot download a song directly without sampling it first.

The 48 songs in the experiment were chosen from bands unknown to participants to minimize any external influence. Furthermore, participants were removed if (i) they had heard about the experiment from one of the bands or their friends had informed them about a specific song or a band, or (ii) they had logged off and reentered the experiment again. The exclusion ensures that the songs are unknown to the participants, nobody participates more than once, and the participants do not hear about the experimental design from other people. This allows us to address two common problems in the field data: (i) consumers' initial prior information is often influenced by word of mouth (WOM) or other external factors, and (ii) consumers may try to conform to what their friends do. More details about the experimental design are provided in Web Appendix E.

3.3. Summary Statistics

Table 1 presents the descriptive statistics of the data used for our analysis. We first focus on the matrix display format, that is, experiment 1 (panel A). In the Independent group, there are 773 participants; the average age is 22.05, 63% of participants are male, and 21% of participants joined the experiment with a dial-up connection. Participants sampled 6.39 songs and downloaded 2.02 songs on average. In the Social Influence group, there are 2,960 participants, the average age is 22.46, 65% of participants are male, and 23% use a dial-

Table 1. Summary Statistics of the Data Used

	Mean	Standard deviation	Min	Max
Panel A: Matrix design				
Independent group (N = 773)				
Songs listened	6.39	8.74	1	48
Songs downloaded	2.02	4.62	0	47
Participant age	22.05	9.35	9	77
Participant male	0.63	0.48	0	1
Internet connection (dial-up)	0.21	0.41	0	1
Social Influence group (N = 2,960)				
Songs listened	6.79	9.20	1	48
Songs downloaded	2.23	4.51	0	48
Participant age	22.46	9.84	9	80
Participant male	0.65	0.48	0	1
Internet connection (dial-up)	0.23	0.42	0	1
Panel B: Column design				
Independent group (N = 1,803)				
Songs listened	9.18	11.44	1	48
Songs downloaded	2.15	5.37	0	48
Participant age	26.10	11.35	10	82
Participant male	0.47	0.50	0	1
Internet connection (dial-up)	0.16	0.36	0	1
Social Influence group (N = 4,004)				
Songs listened	7.10	9.20	1	48
Songs downloaded	2.53	5.54	0	48
Participant age	22.28	10.07	11	81
Participant male	0.35	0.48	0	1
Internet connection (dial-up)	0.24	0.43	0	1

up connection. On average, participants sampled 6.79 songs and downloaded 2.23 songs.

We now turn to the column display format, that is, experiments 2 and 3 (panel B). In the Independent group, there are 1,803 participants, the average age is 26.1, 47% of participants are male, and 16% use a dial-up connection. On average, participants sampled 9.18 songs and downloaded 2.15 songs. In the Social Influence group, there are 4,004 participants, the average age is 22.28, 35% of participants are male, and 24% use a dial-up connection. On average, participants sampled 7.1 songs and downloaded 2.53 songs.[8]

3.4. Preliminary Evidence

On average, participants sampled and downloaded 12.5% and 4% of songs, respectively. This indicates that participants face a significant search cost. In addition, Figure 2 displays the distribution of the maximum number of songs sampled by participants in each condition. Notably, there is significant heterogeneity in participants' search behavior. More specifically, 48.67% sampled fewer than four songs, and 1.59% sampled all 48 songs. This motivates us to allow for heterogeneous search costs in our model.

By examining participants' sampling and downloading decisions in the Independent groups where no social influence is present, Figure 3 provides reduced-form evidence for the position effect. Figure 3, (a) and (b) illustrates the clickthrough rate (i.e., sampling rate) for different positions, representing the proportion of participants who sampled a song at each specific position. In the matrix format, it is assumed that participants read from the first column on the left, top to bottom, before moving to the next column.[9] It is clear from Figure 3, (a) and (b) that songs in higher positions are sampled more frequently. The decreasing trend in CTR with increasing song positions indicates that a song's position significantly influences participants' sampling behavior. This pattern suggests a strong positional effect, where songs placed higher in the list receive more attention and sampling from participants.

In Figure 3, (c) and (d), we display the conversion rate (i.e., downloading rate) of a position, which is the download ratio of the sampled songs by participants in that position. Recall that the experimental design requires participants to sample a song before downloading it. The conversion/download rate of the sampled songs is quite stable across positions. This suggests that a song's position has very little impact on

Figure 2. (Color online) Distribution for the Maximum Number of Songs Sampled by Participants

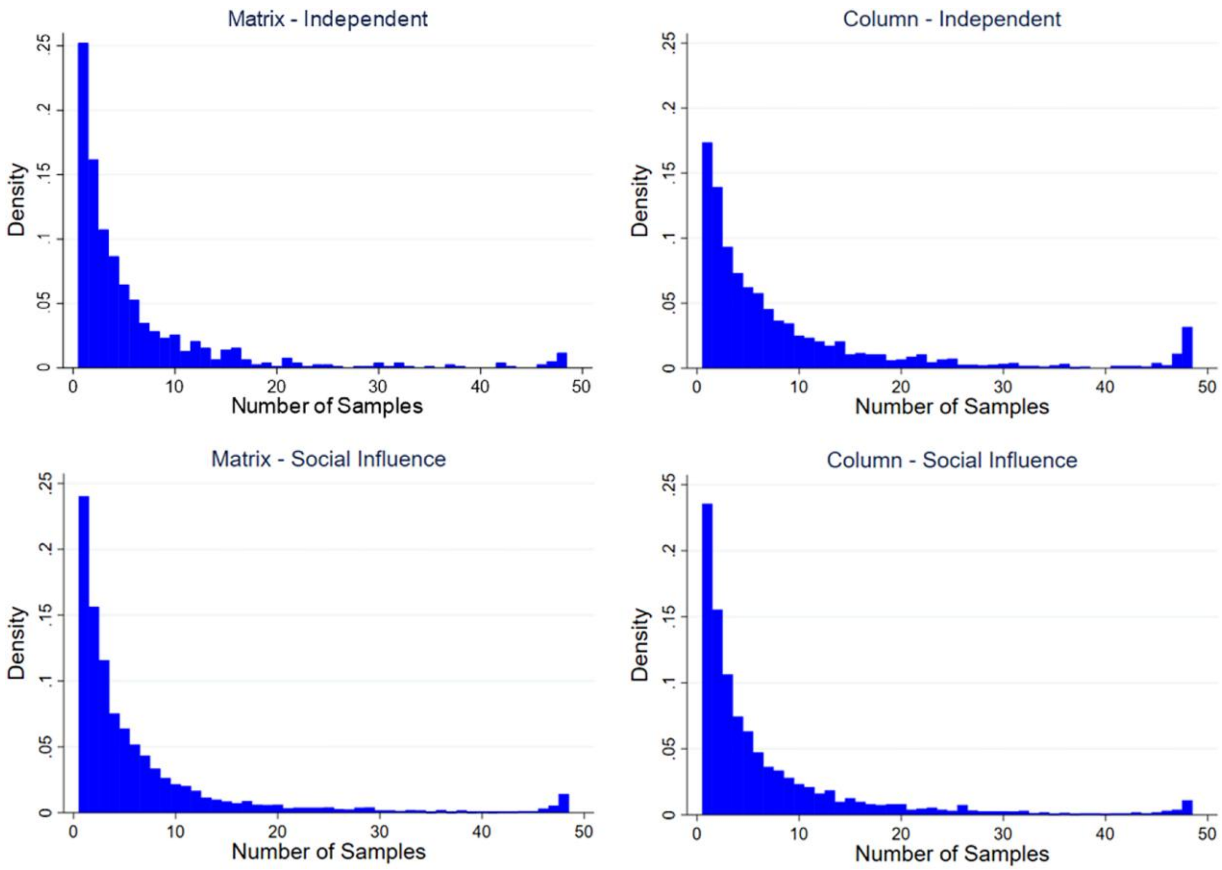
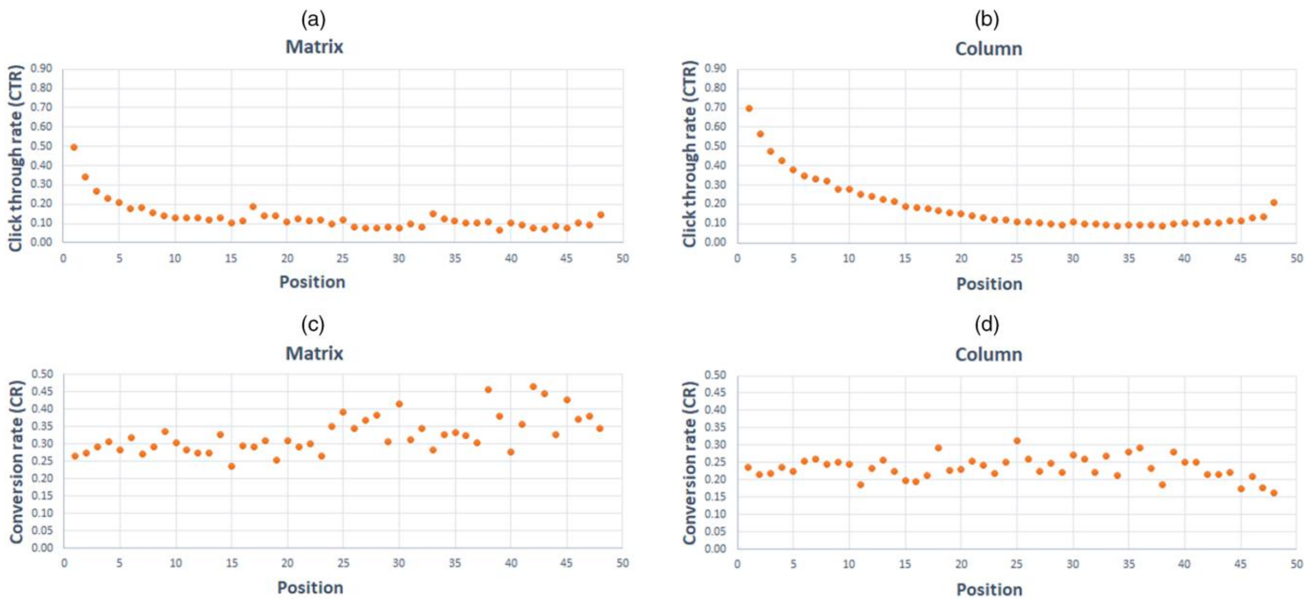


Figure 3. (Color online) Clickthrough Rate and Conversion Rate by Product Position: Independent Group

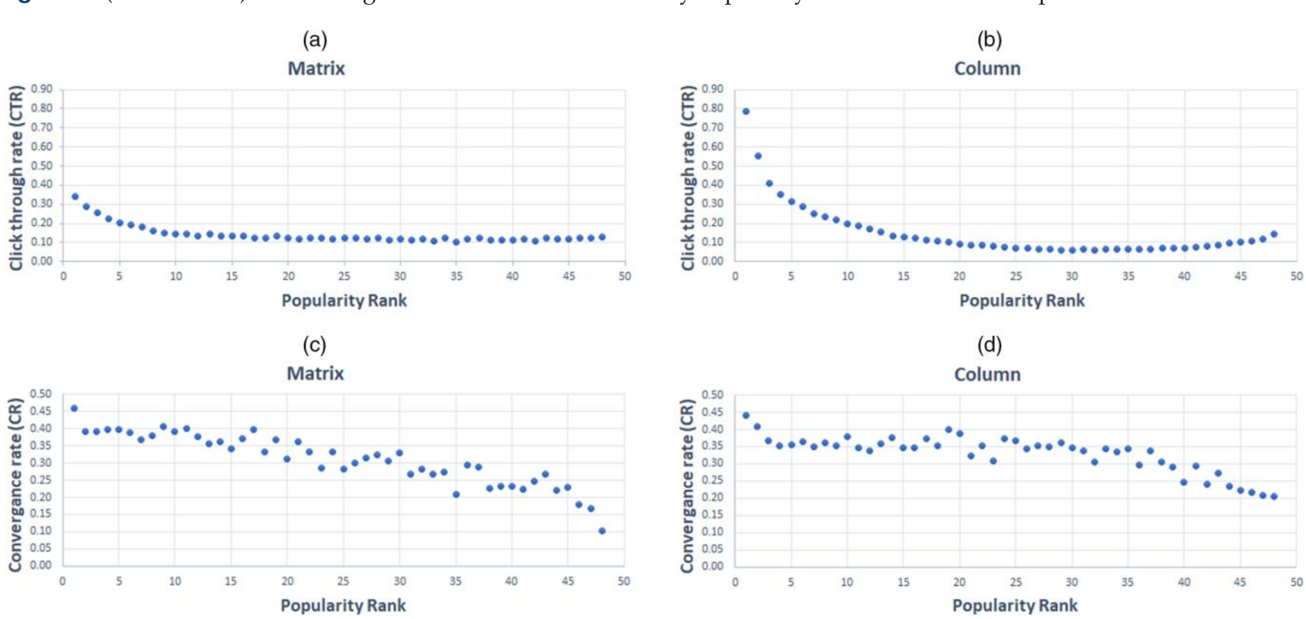


download decisions conditional on sampling, and it only affects the participants' search cost (Ursu 2018).[10]

Figure 4 shows the relationship between clickthrough/sampling rate and conversion/download rate relative to the popularity ranking within the Social Influence group. This figure offers two insights. Firstly, Figure 4, (a) and (b) reveals that popular songs tend to be sampled more frequently, consistent with the idea that a more popular product is usually perceived to have higher quality (Cai et al. 2009, Ching 2010, Zhang 2010, Hendricks et al. 2012, Newberry 2016). This is the case even if we just focus on the matrix format, that is, experiment 1, where songs are randomly sorted in the Social Influence group (see Figure 4, (a) and (c)). Moreover, such a perception is consistent Figure 4, (c) and (d), which shows that a song's conversion rate is positively correlated with its popularity.

Secondly, a comparison between the top two panels in Figures 3 and 4 suggests that individuals prefer sampling songs with higher positions and popularity. This is the case even if we just focus on the matrix display format (experiment 1) where songs are always randomly sorted even in the Social Influence groups, and hence, product position and popularity are independent.

Figure 4. (Color online) Clickthrough Rate and Conversion Rate by Popularity: Social Influence Group



This indicates that when the positions of songs are arranged based on popularity, as in column display format (experiments 2 and 3), disentangling the impacts of position and social influence becomes difficult. Thus, the confounding effects of position and social influence inherent in the column display format within Social Influence groups create an identification challenge.

Finally, we present some reduced-form evidence on how previous downloading outcomes may influence participants' continued sampling behavior on the MusicLab platform. Participants may adjust their sampling behavior based on their success rate in discovering high-quality songs. For instance, if a participant samples the first song, likes it, and downloads it as a high-quality song, she may become more optimistic about the remaining songs. Conversely, if the initial songs do not meet her expectations, she may become pessimistic about the quality of the remaining songs and decide to exit the platform. This behavior significantly impacts one's search behavior, particularly deciding whether to continue or quit sampling.

Table 2 presents the results of a logit regression analysis on the likelihood of exiting the MusicLab platform. We define the feedback variable for participant i at search step t as follows:

$$feedback_{it} = \frac{TP_{it} - TN_{it}}{TP_{it} + TN_{it}},$$

where TP_{it} and TN_{it} represent the cumulative number of songs liked (i.e., downloaded) and disliked (i.e., not downloaded) by participant i, respectively, up to step t of the search. This measure captures the net valence of the participant's experience so far, with positive values indicating a predominance of liked songs and negative values indicating more frequent dislikes. This feedback measure summarizes participants experiences up to each point in the search, capturing whether they have mostly encountered songs they like or dislike. It allows us to examine how prior outcomes shape ongoing search behavior. The regression in Table 2 also controls for participant characteristics such as age, gender, and internet connection type, and it includes dummy variables for the specific experiment the participant was part of.

Table 2. Logit Regression Analysis of Exit Decision Based on Feedback

Variable	Independent group	Social Influence group
$feedback_{it}$	−0.967***	−1.010***
	(0.045)	(0.024)
age_i	−0.019***	−0.028***
	(0.002)	(0.001)
$dial-up_i$	0.990***	0.987***
	(0.064)	(0.035)
$male_i$	0.078**	0.035
	(0.047)	(0.029)
$intercept$	−1.959***	−1.803***
	(0.077)	(0.044)
Experiment dummy	✓	✓
Number of observations	21,488	48,511

Note. Robust standard errors are shown in parentheses.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

This reduced-form evidence indicates that participants who experience lower download success (i.e., lower $feedback_{it}$) in previous search steps are more likely to exit the platform. To capture this behavior, we incorporate this feedback variable into our structural model, accounting for the impact of past outcomes on future sampling decisions.

4. Model

4.1. An Application of the Generalized Weitzman Model

In the well-known sequential search model developed by Weitzman (1979), an agent called Pandora is presented with n boxes. For $j = 1, \ldots, n$, box j contains a prize x_j that comes from an independent probability reward distribution F_j known to Pandora. Pandora can pay a cost c_j to open box j and observe its prize, denoted as x_j^o.[11] Weitzman (1979) shows that the optimal solution for the Pandora problem is to open the boxes in the descending order of their reservation values (selection rule) until the maximum realized prize found is greater than the reservation value of any unopened box (stopping rule). As noted in the literature review, this model has been commonly applied to estimate consumers' sequential search behavior in economics and marketing (e.g., Kim et al. 2010, 2017; Ursu 2018; Ursu et al. 2024).

Despite its foundational contributions to search theory, a key limitation of the classic Weitzman model is its inability to account for multi-item selection within a single search session. In our data set, an average participant sampled seven songs and downloaded two songs in our context. To allow a decision maker to choose multiple items in a search session, we apply one specification of the *generalized Weitzman model* developed by Olszewski and Weber (2015a, b). We first describe the general model below and then specify its elements to capture our MusicLab environment. Then, we explain how to extend it to an estimable structural model in Section 4.2.

Following Olszewski and Weber (2015a, b), we let S be the set of opened boxes, $\vec{x}_S^o = (x_l^o; l \in S)$ be the vector of observed prize values from boxes in S, and $u(\vec{x}_S^o)$ be the utility function, which is increasing in $\vec{x}_S^o$. Similar to Weitzman (1979), the agent's goal is to maximize the following expected net utility:

$$R(\vec{x}_S^o) = u(\vec{x}_S^o) - \sum_{j \in S} c_j. \tag{1}$$

The main departure from Weitzman (1979) is that the agent can gain utility from a combination of the observed prizes rather than just the maximum of the observed prizes.[12] Olszewski and Weber (2015a, b) show sufficient conditions for $u(.)$ such that the following strategy leads to the optimal sequential search behavior.[13]

Consider $j \notin S$, where S is the set of previously opened boxes. The *reservation value* for box j, x_j^* is defined as the smallest prize such that Pandora is indifferent between opening box j and stopping the search:

$$x_j^* = min\{z : u(\vec{x}_S^o, z) \geq -c_j + \mathbb{E}[u(\vec{x}_S^o, x_j^o, z)], z \geq 0\}, \quad (2)$$

where the expectation is taken over x_j^o with the distribution F_j. Here, z denotes any nonnegative real number that can be added to the set of rewards in S. Unlike the reservation value in Weitzman (1979), x_j^* is a function of not only c_j and F_j but also $\vec{x}_S^o$, that is, the vector of all observed prizes before opening box j. Therefore, after opening a box, the reservation values of all the unopened boxes must be recomputed from Equation (2). This shows that the agent receives a combined utility of all opened boxes in the search process. Olszewski and Weber (2015a, b) derive conditions for $u(.)$, under which the optimal strategy is to open boxes in descending order of reservation values until there is no unopened box with reservation values greater than zero.

Now, we consider a specification of the above model outlined in Olszewski and Weber (2015a) (their example 1 and theorem 3) and apply it to our MusicLab context. Let F_{ij} be consumer i's presearch belief distribution about the chance of finding a high-quality song in box j. To simplify notations, we will drop the i subscript below. We assume that F_j is a two-point distribution such that x_j^o is either zero or one with probabilities q_j and $p_j = 1 - q_j$, respectively. In this context, $x_j^o = 1$ indicates that the participant finds a high-quality song after sampling it (i.e., she clicked and listened to it; she liked the song and downloaded it), whereas $x_j^o = 0$ indicates a low-quality song (i.e., she clicked and listened to it; she disliked the song and did not download it). We assume that if the participant discovers a high-quality song, she will download it immediately.[14] After the download decision, she may either continue searching on the main page or log off from the MusicLab platform.

We further assume that $u(.)$ is an increasing concave function of the total number of prizes found. Consider the objective function

$$R(\vec{x}_S^o) = u\left(\sum_{j \in S} x_j^o\right) - \sum_{j \in S} c_j. \quad (3)$$

Equation (3) shows that the agent receives a utility of the sum of the observed prizes $\sum_{j \in S} x_j^o$, that is, the combined utility from all downloaded items in a search session minus the total search costs, $\sum_{j \in S} c_j$. In contrast to the Weitzman model, the participant received a utility of a total number of high-quality songs in Equation (3). Here, the concavity of $u(.)$ captures the concept of diminishing marginal utility in downloading another song. The assumption that payoffs of search outcomes are linearly additive, and $u(\cdot)$ is concave implies that rewards for songs are substitutes and are exchangeable.

Olszewski and Weber (2015a, theorem 3) show that in this particular specification of the model, the optimal solution takes the following form: for any binary reward distribution F_j and any concave utility $u(.)$, the reservation value becomes

$$x_j^* = \max\left\{0, \frac{w_{k+1} - c_j/p_j}{w_{k+1} - w_{k+2}}\right\}, \quad (4)$$

where $w_i = u(i) - u(i-1)$, and k denotes the total number of prizes that have already been found.[15] Suppose that we have n unopened boxes, and we sort these boxes in descending order according to their reservation values: $x_1^* \geq x_2^* \geq \cdots \geq x_{n-1}^* \geq x_n^*$. Without loss of generality, this ordering is equivalent to $p_1/c_1 \geq p_2/c_2 \geq \cdots \geq p_n/c_n$. For simplicity, we use $x_j^* = \frac{p_j}{c_j}$ as the reservation value of box j.

The optimal selection rule is to open boxes in the order of $1, 2, \ldots, n$, and stop according to the following stopping rule:

$$\begin{aligned} &u(k) \geq \mathbb{E}[u(\vec{x}_S^o \cup \{j\})] \\ &\quad \Longleftrightarrow u(k) \geq -c_j + p_j \cdot u(k+1) + (1 - p_j) \cdot u(k), \end{aligned} \quad (5)$$

or equivalently,

$$\frac{1}{x_j^*} = c_j/p_j \geq u(k+1) - u(k) = w_{k+1}. \quad (6)$$

Here, $\mathbb{E}[u(\vec{x}_S^o \cup \{j\})]$ denotes the expected search utility by adding box j to $\vec{x}_S^o$ (which is the vector of the prizes that have been observed), and $u(k+1) - u(k)$ represents the expected marginal gain conditional on box j having a reward (i.e., $x_j^o = 1$). Note that the stopping rule depends on the total number of high-quality songs that the agent has found so far.

The reservation value $x_j^* = p_j/c_j$ has an intuitive interpretation: a participant seeks to maximize her expected utility by opening these boxes and receiving rewards (i.e., sampling and downloading songs). She endures a cost c_j for opening box j, where she will find a reward (i.e., $x_j^o = 1$) with probability p_j. These boxes differ in the probability of providing a reward to a participant (i.e., a high-quality song). Thus, boxes with higher p_j/c_j will be more beneficial for the participant to search first. Therefore, the participant will start by opening the box j with the greatest reservation value $x_j^* = p_j/c_j$ and continue searching until the expected benefit of opening the next box is lower than the cost of opening that box; that is, $1/x_j^* < u(k+1) - u(k)$ if p_j remains unchanged in the search process. In the next subsection, we will extend the above model to a structural empirical setting by specifying $u(.)$, p_j, and c_j to capture participants' search behavior on MusicLab.

4.2. Empirical Model Specification

We first specify the search costs. Figure 3 demonstrates that participants are more likely to sample songs at higher positions. Moreover, it suggests that, conditional on being sampled, the song's position does not affect its download probability. Thus, we model the agent's search cost as a function of the song's position. We follow Kim et al. (2010) and Ursu (2018) to specify the search cost of song j for participant i as

$$c_{ij} = exp(\alpha_i + \beta \cdot Position_{ij}), \tag{7}$$

where the mean search cost component α_i captures the opportunity cost of time listening to any song, and β captures the position effect of song j.[16]

Recall that Figure 2 provides evidence that there is significant heterogeneity in participants' search costs. This could be attributed to participants' individual characteristics, internet connections, or unobserved heterogeneity. Hence, we model α_i as

$$\alpha_i = \alpha_{i0} + \alpha_1 \cdot age_i + \alpha_2 \cdot male_i + \alpha_3 \cdot dial-up_i,$$
$$\alpha_{i0} \sim N(\alpha_0, \sigma^2_{\alpha_0}), \tag{8}$$

where α_{i0} captures the unobserved heterogeneity in participants' search costs, age_i is the participant's age, $male_i$ is a dummy variable which equals one if the participant is male, and $dial-up_i$ is a dummy variable for dial-up connection. Because a dial-up connection has a lower speed, it can increase one's search cost.

A participant can sample a song to see whether she likes it or not. If participant i likes song j, she will download it and receive the reward $x^o_{ij} = 1$ (i.e., it is high-quality). On the contrary, if she dislikes it, she will not download it and will receive the reward $x^o_{ij} = 0$ (i.e., it is low-quality). Let t index the sampling sequence. We set $u(.) = \sqrt{.}$ in the estimation.[17] It follows from Equation (3) and the realizations of x^o_{ij} that $u(\sum_{j\in S} x^o_{ij}) = \sqrt{\sum_{j\in S} x^o_{ij}} = \sqrt{k}$, where k denotes the number of liked songs discovered up to the current search step t; that is, k songs have been downloaded.

Before sampling song j, participant i believes that she will like it with probability p_{ijt}, which we refer to as her *presearch belief probability*. We model p_{ijt} as a logit function of observable information about song j before sampling and her experiences with previously sampled songs:

$$p_{ijt} = \frac{exp(\gamma_0 + \gamma_1 . feedback_{it} + \gamma_2 . appeal_j + \gamma_3 . popularity_{ij} + \delta_j)}{1 + exp(\gamma_0 + \gamma_1 . feedback_{it} + \gamma_2 . appeal_j + \gamma_3 . popularity_{ij} + \delta_j)}, \tag{9}$$

where γ_0 captures the participant's initial belief about the average likelihood of the platform's songs being high quality, $feedback_{it}$ is the participant i's experience from her previously sampled songs, $appeal_j$ is the average attractiveness of a song because of its name and band, $popularity_{ij}$ is song j's number of downloads by previous participants who arrived before participant i, and δ_j is song j's fixed effect.

Two key points should be noted. First, we allow participants' preferences to be heterogeneous. This is why p_{ijt} and x^o_{ij} are participant i specific. In particular, a song can be liked by some participants but disliked by others. Second, $popularity_{ij}$ does not depend on t in Equation (9) because it does not change during participant i's search session; moreover, it only applies if participant i is in a Social Influence group.

The parameter γ_3 measures the effect of $popularity_{ij}$. This is our main parameter of interest because it captures the social influence effect on search behavior. Intuitively, a song's popularity can be an "informative signal" for its quality. As shown in Figure 4, the higher the popularity, the more likely participants would sample it. This indicates that a participant's belief about her chance of liking the song may increase with its popularity.

A participant may change her presearch beliefs about her match value with the remaining songs' according to the rewards discovered so far, as shown in Table 2. Recall that we model $feeback_{it} = \frac{TP_{it} - TN_{it}}{TP_{it} + TN_{it}}$, where TP_{it} (respectively, TN_{it}) denote the total number of songs liked (respectively, disliked) by participant i up to the t-th step of the search. Our approach to model the updating of beliefs from past outcomes aligns closely with *adaptive learning*, as in Doraszelski et al. (2018) and Li and Ching (2024).[18]

We also control for the intrinsic appeal of a song to accurately assess the impact of other factors, such as position or social influence. As in Krumme et al. (2012), we model *appeal* as follows:

$$appeal_j = l_j \Big/ \sum_k l_k, \tag{10}$$

where l_j denotes the total number of times that song j has been sampled in the Independent group. Intuitively, $appeal_j$ captures the average sampling rate of song j when there is no social influence, and songs are randomly positioned. Thus, if song j has a higher appeal compared with song j' (i.e., $appeal_j > appeal_{j'}$), then, on average, song j is more attractive for all participants because of features other than its position. In this case, a song's appeal should only depend on its name and the band because these are the only observable characteristics before sampling songs in the Independent group. The parameter γ_2 captures the effect of the overall appeal of song j.[19]

Note that one key distinction between our empirical structural model here and Olszewski and Weber

(2015a, b)'s theoretical model in Section 4.2 is that p_{ijt} depends on the search step t in our model, whereas it remains static in Olszewski and Weber (2015a, b). It is straightforward to show that the optimality remains valid using induction on t based on $x^*_{ijt} = p_{ijt}/c_{ij}$ because x^*_{ijt} is the corresponding reservation values of boxes at step t. In other words, the reservation values need to be recomputed after each search in our model, and the optimality goes through if this is done at each search step t.

Remarks. We should make three remarks about our model.

1. Our model allows consumers to choose multiple items per search. This raises the issue of whether products are substitutes or complements. Note that each artist only has one song in our MusicLab environment, and hence, it seems unlikely that songs in MusicLab generate complementarity.[20] This is why we model the utility function as concave in $\sum x^o_j$, implying songs are substitutes.

If all products are complements, the utility function will be convex in $\sum x^o_j$. In the case of constant search cost, it is straightforward to see that the convex utility function can lead consumers to search for every item in the platform. In the case where search cost increases with product position (e.g., the lower the product is placed, the higher the search cost, as our estimates show), the stopping rule will depend on the relative convexity of the utility and search cost function. If the marginal search cost increases faster than the marginal utility, our conjecture is that the stopping rule in Equations (5) and (6) will likely still apply.

Even though some items can be complements, we believe that in most cases, diminishing returns of marginal utility will eventually set in after consuming up to a certain point. Hence, it is essential to study the case of concave utility function.[21]

2. We do not impose a *rational expectation* assumption (i.e., we do not impose the restriction that p_{ijt} is the same as song j's actual download probability by participant i). We believe it is unlikely that the rational expectation assumption will hold in our setting because MusicLab only features new songs from new independent artists. All participants can see is the song name, band name, number of downloads per song prior to their arrival, and their own past experiences with the songs that they have sampled ($feedback_{it}$). The experiments have taken steps to ensure that the participants do not have any knowledge about these songs and bands. In this environment, it seems implausible that participants can form rational expectation in the experiments. This is in contrast to a long-existing environment where consumers have many repeated interactions, which may lead to convergence to rational expectation equilibrium behavior. That is why we model participants to form p_{ijt} using adaptive learning via $feedback_{it}$.

3. Although we assume reward to be either zero or one in our model, this restriction can be relaxed, as the theorem (theorem 3) proved by Olszewski and Weber (2015a) considers a more general reward function.[22] However, for our purpose, we do not see much value in going beyond rewards $\in \{0, 1\}$. This is because we only observe whether consumers keep searching or not, which song they choose to sample, and whether they download the song after they have sampled it—all these decisions are binary or discrete choices. Hence, even if we model continuous utility, we still need to convert it to the probability of some discrete decisions. Because we do not observe (or have any proxy for) how much participants enjoy a song after downloading it, we simply do not have the data to infer the actual reward value of each song. This is why we prefer a simpler model by assuming rewards to be either zero or one and focus on modeling p_{ijt} to be a continuous function of some product characteristics. However, if researchers have data on the value of the rewards, the general model proposed in Olszewski and Weber (2015b) can still be applied.

5. Estimation and Identification

We will first discuss our estimation strategy to disentangle the product position and popularity effects. Then, we discuss the identification of the remaining parameters.

5.1. Identification of Product Position and Popularity Effects

Many platforms sort products based on their popularity, as in the column display format/Social Influence group of our experiment. If individuals prefer sampling from top positions and more popular products (see Figures 3 and 4), these confounding effects pose a challenge to separately identify the position and social influence effects in practice.

5.1.1. Two-Step Estimation for Column Display Experiments. Typically, experiments are designed so that one can identify the treatment effect in a straightforward manner using regression analysis or some other simple techniques. Consistent with the goal of providing evidence to show that social influence can impact products' market shares, the experiments of Salganik et al. (2006) employed this standard approach. The Social Influence group is their treatment group, and the Independent group is their control group. However, they made no attempt to model and disentangle the product position and social influence effects in the consumer search process.[23]

Our key insight is that their experimental setup for column format provides a unique opportunity to address the above identification problem. Because songs in the

Independent group are randomly sorted without displaying any popularity information, the data under this condition can be used to estimate the product position effect in the search model (via the search costs). The estimated position effect from the Independent group allows us to control its impact on search behavior under Social Influence groups.[24] Hence, by holding the position effect and search cost parameters fixed when we estimate the model using only the social influence group data, we can identify the social influence effect from the search behavior not explained by the position effect.

This motivates us to use a two-step approach to estimate our structural search model. In step 1, we estimate the position effect (β) along with other search cost parameters (α's) and presearch belief parameters (γ's) by *only* using the Independent group data. This determines the search cost function on the platform, especially the position effect β. In step 2, we take the parameter estimates of the search costs obtained in step 1 as given and then reestimate the presearch belief parameters (γ's), which include the social influence effect (i.e., γ_3), by *only* using the Social Influence group data. This two-step estimation procedure allows us to disentangle the confounding effects of position and social influence.[25]

5.1.2. One-Step Estimation for Matrix Display Experiment. Another way to solve the identification problem is to randomly sort songs independently of their popularity in the Social Influence group. Salganik's experiment 1 did just that. Although this experiment only considers the matrix display format, in this situation, we can estimate both product position and social influence effects simultaneously in one step. However, using a one-step estimation approach instead of the two-step method described above can lead to misleading estimates in the column format/Social Influence group (i.e., experiments 2 and 3) because it doesn't handle the confounding effects of position and popularity. We will revisit this point when we discuss the estimation results.

To check the robustness of our results, we compare the one-step and two-step estimation results under each display-social information disclosure condition. The comparison also provides evidence of how well the two-step method can address the aforementioned identification issue. Table 3 presents all estimation results under one-step and two-step approaches. As expected, the results for the matrix display design reveal that the effect of position and social influence in the one-step and two-step estimation results are similar; this is because there is no confounding issue due to the random sorting of songs in both Independent and Social Influence groups.

However, we observe significant differences in the position and social influence effects between one-step and two-step estimation results in the column design. Specifically, the one-step approach yields an insignificant effect of position, which is counterintuitive and contradicts the reduced-form evidence indicating that participants sample top positions more frequently (see Figure 3), whereas the position effect is positive and significant in the two-step approach. Moreover, the social influence effect is significantly larger in the one-step estimation, with a value of 0.029 compared with 0.019 obtained in the two-step estimation.[26] We take this as evidence that the two-step approach is able to address the multicollinearity issue.

Lastly, our two-step identification strategy relies on the availability of both Independent and Social Influence groups to separately estimate the effects of position and social influence. However, in practice, platforms may not always have access to an Independent group where social influence is not disclosed. We acknowledge this limitation in certain practical scenarios. However, if platforms can randomly sort items regardless of their popularity, our structural model can still be estimated using a one-step approach without the need for an Independent group.

5.1.3. Identification of Other Parameters. Besides the product position and social influence effects, the other parameters can be identified straightforwardly because of the presence of exogenous variation in the data. Note that γ_0 in presearch belief has the same effect as α_0 in search costs in terms of participants' search behavior. Intuitively, either lower base search cost (i.e., $\alpha_0 \downarrow$) or a higher base prior belief for a song being high quality (i.e., $\gamma_0 \uparrow$) leads to more searches. Mathematically, α_0 and γ_0 can move the reservation values $x^*_{ijt}(= p_{ijt}/c_{ij})$ in the same direction, with γ_0 through the numerator (p_{ijt}) and α_0 through the denominator (c_{ij}). Thus, we need to normalize one of them and estimate the other. Here, we fix $\gamma_0 = 0$ and estimate the rest of the parameters. Finally, it is worth noting that the identification of the appeal and popularity effects rely on the cross-sectional variation in the data. However, the feedback effect is identified from both cross-sectional and within-subject variation over time. This stems each participant's own experience of sampling songs and subsequent download decisions.

5.2. Estimation

There are three sets of parameters to be estimated in the model: (i) participant-specific search cost parameters, denoted as $\vec{\alpha} = (\alpha_0, \sigma^2_{\alpha_0}, \alpha_1, \alpha_2, \alpha_3)$; (ii) the song-specific search cost with respect to the position effect β; and (iii) the participant's presearch belief probability parameters $\vec{\gamma} = (\gamma_0, \gamma_1, \gamma_2, \gamma_3)$. Suppose participant i sampled s songs of the total $J = 48$ songs displayed on the platform.

Let $R_i = \{R_i(1), \ldots, R_i(s)\}$ denote the set of the sampled songs' positions and the order in which they were sampled. For example, if participant i sampled three

Table 3. Estimation Results

	Matrix			Column		
		Social influence			Social influence	
Parameters	Independent	Two-step	One-step	Independent	Two-step	One-step
			Panel A: Search cost			
α_0	-1.54^{***}	-1.54^{***}	-1.53^{***}	-1.59^{***}	-1.59^{***}	-1.48^{***}
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
σ_{α_0}	0.37^{***}	0.37^{***}	0.41^{***}	0.41^{***}	0.41^{***}	0.43^{***}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\alpha_1(age)$	-0.002^{**}	-0.002^{**}	-0.002^{***}	-0.003^{***}	-0.003^{***}	-0.002^{***}
	(0.0010)	(0.0010)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
$\alpha_2(gender)$	-0.06^{***}	-0.07^{***}	-0.06^{***}	-0.04^{***}	-0.04^{***}	-0.03^{***}
	(0.02)	(0.02)	(0.012)	(0.01)	(0.01)	(0.010)
$\alpha_3(dial\text{-}up)$	0.27^{***}	0.27^{***}	0.20^{***}	0.22^{***}	0.22^{***}	0.22^{***}
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
$\beta(position)$	0.0006^{***}	0.0006^{***}	0.0006^{***}	0.0010^{***}	0.0010^{***}	0.0001^{*}
	(9.2E-05)	(9.1E-05)	(5.0E-05)	(5.2E-05)	(5.2E-05)	(6.2E-05)
			Panel B: Presearch belief			
γ_0	0	0	0	0	0	0
$\gamma_1(feedback)$	1.24^{***}	1.20^{***}	1.17^{***}	1.28^{***}	1.19^{***}	1.05^{***}
	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)
$\gamma_2(appeal)$	0.008^{***}	0.007^{***}	0.006^{***}	0.005^{***}	0.003^{***}	0.004^{***}
	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
$\gamma_3(popularity)$		0.009^{***}	0.009^{***}		0.019^{***}	0.029^{***}
		(0.000)	(0.001)		(0.001)	(0.001)
Log likelihood	−5,098	−19,695	−19,646	−12,637	−25,602	−25,284
Observations	37,104	142,080	142,080	86,544	192,192	192,192

Note. Robust standard errors are shown in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

songs sequentially (i.e., $s = 3$) at positions 3, 20, and 8, then $R_i(1) = 3$, $R_i(2) = 20$, and $R_i(3) = 8$, respectively. Note that we observe R_i for each participant in our data. Given $F_{ijt} \sim Bern(p_{ijt})$ and utility function $u(k) = \sqrt{k}$ described in Section 4.2, participant i's optimal sequential search strategy translates into the following three restrictions.

First, the selection rule requires that participant i samples songs in the descending order of their reservation values $x^*_{ijt} = p_{ijt}/c_{ij}$. Therefore, if song j is sampled at the t-th search step, its reservation value must be greater than the reservation values of the unsampled songs. Let S'_{it} denote the set of songs not sampled by participant i up to t-th search. Formally, we have

$$C1 := x^*_{ijt} \geq \max_{\eta \in S'_{it}} \{x^*_{i\eta t}\}, \quad \forall t \in \{1, \ldots, s\}. \tag{11}$$

Second, if song j is sampled at the t-th search, its expected benefit must be greater than the cost of sampling it; otherwise, the participant should have stopped searching. Therefore, we have

$$C2 := 1/x^*_{ijt} \leq w_{k+1}, \quad \forall t \in \{1, \ldots, s\}, \tag{12}$$

where $w_{k+1} = u(k+1) - u(k)$, and k is the number of downloaded songs until the t-th search step. Again, note that w_{k+1} is the marginal gain conditional on song j being a high-quality song to be downloaded by participant i; that is, participant i has $k+1$ high-quality songs in her library by adding song j.[27]

Finally, if participant i has downloaded K songs in total before stopping the search session (i.e., leaving the platform at the s-th search step when downloading K songs), the stopping rule will imply that the expected benefit of sampling those songs not searched by participant i (marginal utility) must be lower than the search cost she would have had. This leads to the following condition:

$$C3 := 1/x^*_{ijt} > u(K+1) - u(K) = w_{K+1}, \quad \forall j \notin R_i. \tag{13}$$

Let P_{iR_i} denote the probability that participant i follows the search sequence R_i observed in the data, given the set of parameters. Then, we have

$$P_{iR_i} = Pr(C1 \cap C2 \cap C3) = \int I(cond)\phi(\alpha_{0i})d_{\alpha_{0i}}, \tag{14}$$

where $I(cond)$ is an indicator for whether Conditions (11), (12), and (13) hold jointly. Thus, the log likelihood over all participants can be written as

$$LL = \sum_i \sum_{R_i} d_{iR_i} log(P_{iR_i}), \tag{15}$$

where $d_{iR_i} = 1$ if participant i has the search sequence R_i; otherwise, $d_{iR_i} = 0$. Because the integral in Equation (15) does not have a closed-form solution, we should use the simulated log-likelihood approach commonly used in the search literature by replacing P_{iR_i} with the simulated choice probability $\hat{P}_{iR_i}$. This leads to the following expression:

$$SLL = \sum_i \sum_{R_i} d_{iR_i} log(\hat{P}_{iR_i}). \tag{16}$$

Multiple approaches are available to determine the above probability $\hat{P}_{iR_i}$. We follow the empirical search models in economics and marketing (Honka 2014, Honka and Chintagunta 2017, Ursu 2018), and use the *logit-smoothed AR simulator*, in which the indicator function $I(cond)$ is replaced with a logit function that has first and second derivatives (McFadden 1989).[28] The logit-smooth AR simulator is implemented as follows:

1. Draw $d = \{1, \ldots, D\}$ samples of α_i^d for each participant to capture unobserved heterogeneity.
2. Use α_i^d to form cost c_{ij}^d with respect to d-th draw.
3. Compute probability of rewards p_{ijt} and the reservation values $x_{ijt}^{*d} = p_{ijt}/c_{ij}^d$.
4. Define the following expressions for d-th draw:
   e. $v_1^d = x_{ijt}^{*d} - \max_{\eta \in S'_{it}} \{x_{i\eta t}^{*d}\}$,
   f. $v_2^d = w_{k+1} - 1/x_{ijt}^{*d}$, and
   g. $v_3^d = 1/x_{ijt}^{*d} - w_{K+1}$.
5. Calculate S^d w.r.t d-th draw using the logit expression

$$S^d = \frac{1}{1 + \sum_{n=1}^{3} e^{-v_n^d/\lambda}}. \tag{17}$$

6. Compute the simulated probability P_{iR_i} by taking the average of the S^d over D draws:

$$\hat{P}_{iR_i} = \frac{1}{D} \sum_d S^d. \tag{18}$$

Note that v_i^d (for any $i = 1, 2, 3$) will be a larger positive value when the condition Ci is satisfied much more strongly given parameters' values; otherwise, v_i^d has a negative value. To put it differently, if participant i follows the R_i sequence search as in Section 4, the S^d and the simulated log-likelihood function SLL will approach one and zero, respectively. This effectively means that we are smoothing the log-likelihood function by using the logit-smooth AR simulator. Consequently, by maximizing SLL, we are able to estimate the set of parameters such that the participants follow the generalized Weitzman sequential model proposed in Section 4.2. Here, λ is called the smoothing scaling parameter. As $\lambda \to 0$, the simulator approaches the AR simulator and is thus unbiased. Hence, the researcher should use a small enough λ that prevents the numerical problems of optimizing with a nonsmooth function. In our case, we chose $\lambda = 1/50$, a value commonly utilized in the search literature, and that also works best in recovering the true parameters in the Monte Carlo simulation (see Web Appendix B for details).[29]

6. Estimation Results

In this section, we provide the estimation results of the structural model, along with a discussion of the key findings. Recall that our identification argument leads to the conclusion that we should apply a two-step method to estimate the model from the column display format (see Section 5.1.1). However, we can also apply a one-step method to estimate the model from the matrix display format/Social Influence group (see Section 5.1.2). For comparison purposes, we apply both one-step and two-step estimation methods to the social influence condition, regardless of the display format. Table 3 summarizes the estimation results. The estimates for the song's fixed effects in the presearch belief model are reported in Web Appendix H.

The two-step estimation for the Social Influence groups deserves more explanation. As explained in Murphy and Topel (2002) and Wooldridge (2014), the standard errors for the parameters obtained in step 1 (i.e., search costs parameters here) are valid for two-step estimation procedures. However, when calculating the standard errors of the parameter estimates obtained in step 2, that is, presearch belief parameters in the Social Influence group, we need to take into account the standard error of the parameter estimates obtained in step 1.

Following Kasahara and Shimotsu (2008), we use the bootstrap method to address this problem. More precisely, we draw 100 bootstrap samples for the search cost parameters from the normal distributions with the mean set at the point estimate and the standard deviation set at the standard error, estimated in the Independent group. For each set of simulated search cost parameters from the bootstrap samples, we fix these parameters and then estimate the presearch belief parameters using the Social Influence group data. The point estimate and standard errors of the parameter estimates in step 2 are the mean and standard deviation of the estimates obtained from the above bootstrap procedure.

We first discuss the two-step estimation results from the column display/Social Influence condition (panel B of Table 3). The estimates of the position effect (β) and the popularity effect (γ_3) are 0.001 and 0.019, respectively, and they are both positive and significant. However, in the one-step estimation results, the position effect becomes much smaller at 0.0001, and it is insignificant at the 5% level; moreover, the popularity effect becomes much larger at 0.029. The counterintuitive results from the one-step estimation of column display/Social Influence illustrate the identification problem that we discussed earlier in Section 5.1.1.

We now turn to discuss the estimation results from the matrix display/Social Influence condition (panel A in Table 3). We start with the one-step estimation results. The estimates of the position effect (β) and the popularity effect (γ_3) are 0.0006 and 0.009, respectively; like the results from the column display format, they are both positive and significant. As a robustness check, we also apply the two-step approach to estimate our model using the data from this condition. In principle, because a song's position and popularity do not confound with each other here, we should still obtain similar results. In fact, this is the case; using the two-step approach, the estimates of the position effect (β) and the popularity effect (γ_3) are 0.0006 and 0.009, respectively, and they are similar to the estimates from the one-step approach. As discussed earlier (see endnote 26), to address the nonlinearity of our model, we further compare the calculated marginal effects instead of point estimates. Our findings remain robust and consistent.

The positive estimate of the position parameter (β) indicates that the search cost is higher for songs at lower positions (i.e., located closer to the bottom of the list). Also, the higher value of β in the column format versus the matrix format (i.e., 0.001 versus 0.0006) suggests that the position effect is stronger in the column format compared with the matrix format. In the column format, participants must scroll down to access lower-positioned songs, whereas in the matrix format, all songs are displayed simultaneously on the screen. Again, the results are robust and consistent if we consider the marginal effects rather than point estimates.

The positive estimate of γ_3 suggests that popular songs are more likely to be sampled by participants. Furthermore, the greater estimate of γ_3 in the column design shows that popularity has a much more pronounced effect on participants' presearch beliefs under column display compared with matrix display. This could be because under the matrix format, all songs are randomly sorted; as a result, it would likely be harder for participants to infer the ranking of songs by their popularity. For intuitive interpretation, we compare the percentage change in presearch belief between column and matrix formats when popularity, measured by the number of downloads, changes by x units. Assuming a song with average appeal and popularity has been sampled by identical participants in both display formats (i.e., holding all cost covariates, positions, and feedback identical at their average levels). If the number of downloads increases by 1, 10, or 100 units, there is a 0.47%, 4.53%, and 21.22% higher chance, respectively, that the song will be considered high quality in the column format compared with the matrix format. This demonstrates the significant impact of social influence on perceived quality in search behavior.

We now turn to discuss other parameter estimates. All the search cost and presearch belief parameter estimates are statistically significant and economically meaningful. The negative estimate of α_1 indicates that older participants have slightly lower search costs and have continued to sample more songs than younger participants. The negative estimate of α_2 indicates that male participants have lower search costs and have sampled more songs on average than their female counterparts. The positive estimate of α_3 shows that participants joining the experiment with a dial-up connection have greater search costs, and consequently, they also sampled fewer songs than others. Finally, $\sigma^2_{\alpha_0}$, which captures the participants' unobserved search cost heterogeneity, is quite large and statistically significant.

For the presearch belief parameters, the positive and statistically significant estimate of feedback (γ_1) captures participants' adaptive learning behavior from sampling songs. This implies that when a participant samples a high-quality song, she will revise her presearch belief that the remaining songs are more likely to be of high quality and vice versa. Importantly, the effect of feedback is about 3.3% and 7.6% higher in Independent groups compared with Social Influence groups in matrix and column format, respectively.

Additionally, we observe a significant positive impact of appeal on presearch belief across all estimation results. This indicates that songs with appealing names are more likely to be sampled during a search session. However, the appeal effect is also much smaller in the Social Influence groups compared with the Independent groups, regardless of the display format. The appeal has 12.5% and 40% less weight in the search behavior conditional on disclosing songs' popularity in matrix and column displays, respectively. Our result is consistent with the consumer behavior literature wherein decision makers may reweight the importance of heuristic clues in a decision process if there is a new information clue in the environment (Payne et al. 1993).

To illustrate the importance of social influence, we reestimate the model from the Social Influence group by setting $\gamma_3 = 0$, and we refer to it as the "No Popularity Model." Table 4 shows our Full Model performance compared with the No Popularity Model. Full Model yields substantial Akaike Information Criterion (AIC) enhancements of 115 and 1,077 for the matrix and column formats, respectively. These results highlight the importance of taking into account the impact of popularity in explaining search behavior data.

We also consider a Random Search Model, where the parameters β, γ_1, γ_2, and γ_3, which capture the effects of position, feedback, songs' appeal, and popularity, respectively, are all set to zero. This model assumes that all songs have identical search costs and presearch belief probabilities of a reward; this implies that participants randomly sample songs with equal probability regardless of their position, appeal, or popularity. Comparing the Full and Random Search models' estimation

Table 4. Model Performance Comparison

	Matrix		Column	
	Independent	Social influence	Independent	Social influence
Log likelihood				
Full model	−5,098	−19,695	−12,637	−25,602
No popularity model	—	−19,754	—	−26,142
Random search model	−5,782	−21,719	−13,997	−29,375
AIC				
Full model	10,214	39,410	25,292	51,224
No popularity model	—	39,525	—	52,301
Random search model	11,576	43,450	28,005	58,763

results in the Independent groups, the Full Model improves the AIC by 1,362 and 2,713 for matrix and column experiments, respectively. Furthermore, comparing the Full and Random Search models' estimation results in the Social Influence groups yields substantial AIC enhancements of 4,040 and 7,539 for the matrix and column formats, respectively. These results underscore the critical role of social influence and popularity in shaping search behavior and highlight the robustness and explanatory power of our model.

7. Counterfactual Analyses

Our structural estimation provides insights into how product popularity and position influence consumer search decisions. By running counterfactuals to evaluate different product assortments and disclosing social influence, platforms can strategically present products to enhance their clickthrough rate, conversion rate, and/or overall user experience.[30]

7.1. Popularity Disclosure and Platforms' Policies

For each display format (column and matrix), we consider four counterfactual experiments to understand the impact of disclosing popularity information under different situations. In the counterfactual experiment CF1, songs are sorted randomly, and participants do not observe their popularity. In the counterfactual experiment CF2, song popularity is revealed, but the sorting remains random. In the counterfactual experiment CF3, songs are sorted based on their displayed popularity, from the most popular to the least. In counterfactual experiment CF4, song popularity is displayed, and songs are sorted individually for each participant based on their predicted likelihood of downloading each song, reflecting their heterogeneous preferences derived from users' characteristics and song's multidimensional content.

In summary, we quantify the impact of all eight (i.e., four counterfactual designs × two display formats) scenarios on three measures of platform performance: (i) the average number of songs being sampled, (ii) the average number of downloads, and (iii) the search efficiency, which is defined as the average of $\frac{\#\text{ downloaded songs}}{\#\text{sampled songs}}$ across participants.

7.2. Advantages of Structural Counterfactual Analyses

We implement our counterfactuals based on the estimated structural model. It has the advantage of predicting outcomes of scenarios that Salganik (2008) did not consider in the actual experiments, including CF2 in the column display format, CF3 in the matrix display format, and all cases considered in CF4. Without conducting new experiments, our structural approach allows us to evaluate these counterfactual scenarios, and possibly more. Moreover, in our counterfactual experiments, we are able to simulate participants' behavior under scenarios to which they were not assigned to in the actual experiments.

Note further that the evolutions of feedback and popularity are endogenous. When we change the way the platform sorts the songs or discloses popularity information, it will affect a participant's decision on which songs to sample and download. This will change $feedback_{it}$ and $popularity_{ij}$; the former will affect within-subject behavior, and the latter will influence across-subject behavior. Our counterfactual experiments explicitly capture such endogenous dynamics.

7.3. Simulating Counterfactual Environments

We use all the participants and their actual demographic for the counterfactual simulations. Although each participant was only assigned to one condition, we simulate their behavior under all counterfactual scenarios. To account for the unobserved search cost for each participant, denoted by α_{i0}, we make 100 draws of α_{i0} for each participant from the normal distribution with parameters estimated from the empirical results in Table 3. Then, we run simulations for each draw and report the average results.

To address possible new dynamics and market outcomes, we use a dynamically updated popularity measure for each participant based on the simulated download behavior of previous participants in that world under the existing counterfactual design. We keep the order in which participants join a counterfactual experiment to be the same as what we observe in the data. Detailed explanations of the simulation procedures and calculations of the results are provided in Web Appendix D.

7.4. Enhancing Counterfactual Simulations Using Machine Learning

For songs that are sampled by participants, we observe whether they download them or not. However, in our counterfactual experiments, participants may select different songs to sample than those chosen in the actual experiments. For songs that are not sampled by a participant in the actual experiments, we do not observe whether they would have downloaded it or not. Hence, we need to predict each participant's download decision for every song. To precisely predict one's download probability, we must consider two critical factors: (i) the songs' attributes, which are unstructured content data to be revealed only after sampling, and (ii) consumer heterogeneity in preferences among participants.

Therefore, we employ a machine learning method known as "content-based filtering," which offers several advantages over traditional models such as logit. It can handle unstructured data more effectively by considering potential interactions through hidden layers of neural networks. Additionally, it adapts to individual user preferences without assuming explicit functional forms, allowing for greater flexibility in modeling user behavior. Moreover, content-based filtering can identify nuanced patterns in user interactions with product attributes, leading to more accurate and personalized predictions.

To apply content-based filtering, we used the participant characteristics from survey data (Web Appendix C, Table A.3) alongside the songs' popularity and extracted unstructured features such as genre, tempo, key, and used instruments (Web Appendix C, Table A.4). We extracted the features of these songs using the Librosa package, a widely used Python tool for analyzing and processing audio signals. By using content-based filtering, we can group participants with similar tastes and forecast their download probabilities for all songs under different counterfactual scenarios.

This method employs neural networks to create user and item vectors, essentially numerical representations of participants and songs based on their preferences and features. Then, these vectors are merged by using a sigmoid activation function, giving us a more accurate prediction of a participant's likelihood to download songs. When compared with a standard logit, content-based filtering performs better in predicting download behaviors for all songs. We discuss the detailed implementation and comparison in Web Appendix C.

We should highlight that we use content-based filtering to model and estimate the probability of downloading after sampling (which can be interpreted as the realized utility after sampling). It differs from the pre-search belief which captures individual's prior belief of whether a song is of high quality before sampling in Equation (9).

This content-based filtering method also facilitates a personalized targeting approach, enabling platforms to sort songs for each participant based on their predicted likelihood of download. This approach allows us to optimize individual-specific item rankings and enhancing user satisfaction and engagement by prioritizing the display of more relevant items in higher positions. This strategy is implemented in our CF4 scenario.

7.5. Counterfactual Results

We evaluate our counterfactual results in three dimensions: (i) l denotes the average number of songs sampled, (ii) k denotes the average number of songs downloaded, and (iii) w denotes the search efficiency, which is the average ratio of the number of downloaded songs to the total number of sampled songs at the individual level. We interpret w as the platform's efficiency in assisting consumers to find more high-quality songs in a search session.

We first discuss the results under column format. In CF1, random assortment without popularity, participants, on average, sampled 8.65 songs and downloaded 1.5 songs with a search efficiency of 0.293. Displaying the popularity of the songs in CF2 increased the average number of songs sampled and downloaded to 9.36 and 1.63, respectively, and raised the search efficiency to 0.336. Thus, disclosing social information increases the platform's search efficiency by approximately 14.7%. In CF3, sorting songs based on popularity enhances the impact of social influence on the search session. On average, participants sampled slightly fewer songs (8.98) but downloaded more songs (1.72), leading to a higher search efficiency of 0.357. Thus, sorting items based on their popularity further boosted the platform's search efficiency by nearly 6.3%. Under CF4 personalized sorting condition, participants sampled even fewer songs (8.14) whereas finding more desired songs to download (2.18), leading to the highest search efficiency of 0.454.

Similarly, under the matrix format, participants sampled an average of 7.76, 8.26, 7.90, and 7.13 songs in CF1, CF2, CF3, and CF4, respectively. The average number of songs downloaded by participants in CF1, CF2, CF3, and CF4 are 1.29, 1.38, 1.44, and 1.76 songs, respectively, with corresponding efficiencies of 0.303, 0.332, 0.348, and 0.436. Thus, under the matrix format, disclosing popularity information increases the platform's search efficiency by 9.6%, sorting items based on their popularity further increases search efficiency by

4.8%, and utilizing personalized sorting leads to the highest search efficiency, improving it by an additional 25.3%.

Interestingly, ranking songs based on their popularity leads to the following asymmetric results in both column and matrix display formats: (i) reducing the average number of songs sampled, and (ii) increasing the average number of songs downloaded, ultimately improving search efficiency. Furthermore, applying personalized sorting enhances this effect even more, as participants sampled fewer songs but downloaded significantly more, achieving the highest search efficiency (0.454 in the column format and 0.436 in the matrix format). This demonstrates that whereas personalized ranking achieves superior search efficiency, it leads to less sampling. This is consistent with the theory that fully personalized targeting is not always optimal in every metric (Moorthy and Shahrokhi Tehrani 2023).

Note that all metrics increase more significantly in the column format compared with the matrix format. Specifically, when sorting songs by their popularity, the number of songs sampled and the number of songs downloaded increase by 13.7% and 19.4%, respectively, and when sorting songs by user preference, the number of songs sampled increases by 14.2% and the number of songs downloaded increases by 23.9% in the column format compared with the matrix format. This is consistent with the concept of "choice overload bias" in consumer behavior. Participants see more alternatives on the screen in the matrix display format compared with the column display format. Intuitively, having too many options can make a decision overwhelming because of many potential outcomes and risks involved with making a wrong choice, leading the decision maker to walk away (Iyengar and Lepper 2000, Shah and Wolford 2007).

7.6. Managerial Implications

Our counterfactuals have implications about how online platforms can increase their profits by implementing more suitable strategies to sort and disclose social influence, depending on their revenue generation models. Note that our counterfactual analysis indicates that keeping everything else the same, the column format has a greater impact compared with the matrix format, as shown in Table 5. Thus, we will discuss the implications under the column format.

- Product sales platforms: Platforms such as 7Digital, which derive revenue from product sales, would be better off adopting a column format where products are ranked according to popularity or personalized user preference, as this approach is likely to result in a higher number of downloads and purchases, thereby enhancing platforms' revenue.
- Subscription-based platforms: Platforms such as Spotify Premium that charge a monthly subscription fee are also advised to use a column format where products are sorted based on their popularity or personalized user preference (if applicable). This design can improve utility and efficiency for consumers, discouraging them from switching to competing platforms. If the platform's goal is to maximize the search efficiency for consumers, our results suggest that under the column format, it is preferable to sort products based on personalized user preference (if applicable) or their popularity, assuming higher search efficiency leads to higher consumer satisfaction.
- Freemium platforms: Platforms such as the free-to-use versions of Spotify or Pandora, which rely on advertising revenue, should consider a column design with random assortment whereas displaying popularity information. With CF2's 4.2% higher sample rate, consumers are encouraged to explore more items and spend more time on the platform. This should generate increased ad impression opportunities.

8. Conclusion

Leveraging a publicly available data set from an online music platform field experiment, this paper contributes to the existing research on online consumer search by disentangling the effects of product position and social influence on consumer search behavior. Our findings highlight the significant impact that these two elements can have on individuals' decision-making processes, reinforcing the need for careful consideration of these elements in digital marketplaces.

Furthermore, by developing a sequential search model that does not restrict to (i) one choice per search session, and (ii) known reward distribution, we address two common limitations of the previous research based on the classic Weitzman model. More specifically, our model captures consumers choosing multiple items per search session by extending Olszewski and Weber (2015a, b) and deviating from known reward distribution by allowing consumers to adaptively learn about their matches with the platform as in Doraszelski et al. (2018) and Li and Ching (2024).

In platforms with restricted presearch information about products' attributes, such as music or short video platforms, users often make initial decisions based on limited cues such as brief titles or the popularity level of items. However, after sampling—such as listening to a portion of a song—consumers encounter a richer set of features that can significantly influence their behavior, including decisions to download. Previous research has abstracted away from these institutional details. To address this, we use content-based filtering to model the interactions between these detailed contextual attributes and user heterogeneous preferences in their download decisions. By combining this download decision model with our structural search model, we are

Table 5. Counterfactual Results

	Matrix			Column		
Counterfactual experiments	Samples (l)	Downloads (k)	Efficiency (w)	Samples (l)	Downloads (k)	Efficiency (w)
CF1: Randomly sorted without popularity	7.76	1.29	0.303	8.65	1.50	0.293
	(0.11)	(0.02)	(0.003)	(0.12)	(0.02)	(0.002)
CF2: Randomly sorted with popularity	8.26	1.38	0.332	9.36	1.63	0.336
	(0.11)	(0.02)	(0.004)	(0.11)	(0.02)	(0.004)
CF3: Sorted based on popularity	7.90	1.44	0.348	8.98	1.72	0.357
	(0.10)	(0.02)	(0.006)	(0.11)	(0.03)	(0.006)
CF4: Sorted based on personalized preference	7.13	1.76	0.436	8.14	2.18	0.454
	(0.11)	(0.02)	(0.003)	(0.11)	(0.03)	(0.003)

Notes. Please refer to Web Appendix D for an explanation of how l, k, and w are calculated. Robust standard errors are shown in parentheses. The t-test reveals significant differences between the relevant variables.

able to conduct counterfactual analyses, offering valuable insights for platform managers. Specifically, platforms generating revenue through sales should use the column format and sort products by personalized user preference or popularity to increase purchases. But platforms relying on advertising revenue should opt for a random assortment and disclose popularity information to increase consumer engagement and advertising opportunities.

Our counterfactual analyses further demonstrate the role of product ranking and social influence in shaping search behavior. By simulating different disclosure and sorting mechanisms, we quantify their impact on search efficiency and engagement. Notably, CF4, which ranks songs based on personalized predicted download likelihood, achieves the highest search efficiency by aligning recommendations with individual preferences. This highlights the potential of personalized ranking strategies in optimizing user experience and platform outcomes.

Our study significantly diverges from previous sequential search models, which are summarized in Ursu et al. (2024). These papers model the difference between presearch and postsearch utility using a random match value from a fixed one-dimensional distribution (see Web Appendix G). We highlight that when modeling platforms for music streaming (e.g., Spotify), short video streaming (e.g., YouTube), etc., users decide whether to sample items with limited initial information, and the multidimensional unstructured attributes of these products are revealed only after sampling. This implies that presearch utility and postsearch utility may involve different sets of product attributes. This is why we have decided to deviate from the previous literature by modeling the sampling and downloading decisions separately.

We conclude by discussing some limitations and suggesting directions for future research. Our study assumes that participants use adaptive learning based on previous outcomes without accounting for the exploration value of learning. Incorporating this aspect is beyond the scope of this paper. We leave it for future research to investigate whether consumers are fully forward looking when making exploration-exploitation trade-offs in search problems, especially when they have the option to choose multiple items.

Moreover, our findings are based on a controlled experiment, which may differ from real-world scenarios. The fact that participants in our experiments were only allowed to search in one session and did not engage in monetary transactions for the downloaded music raises questions about the internal versus external validity of our results. Addressing these issues would require future studies to conduct field experiments on actual platforms to better capture new insights. Another caveat of our analysis is that we assume the consumers' structural parameter associated with song position remains unchanged in counterfactual scenarios. In practice, if platforms alter the algorithm used for sorting songs, consumers may adapt, leading to a change in that structural parameter in the long run. As in Compiani et al. (2024, p. 621), we view our counterfactual analysis as best suited in the short-to-medium run before consumers react to those sorting algorithm changes if they are not publicized.

Our model makes several assumptions tailored to the MusicLab context, notably that consumers make immediate download decisions upon sampling and that songs are substitutes in the utility function. These assumptions are empirically justified in our setting. However, such conditions may not apply to other environments. For instance, the payoffs of each item can be more general and take a large number of possible values. In such settings, consumers may defer purchase decisions until after sampling multiple items (e.g., via shopping carts). Another example is that items are complements (e.g., songs from the same album or episodes in a series). The selection and stopping rule proposed in the generalized Weitzman model by Olszewski and Weber (2015a) may not be optimal in these examples. Addressing these environments would require new structural frameworks that incorporate deferred choice and complementarity in utility. We leave them for future research.

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Endnotes

[1] For instance, Amazon and Expedia arrange products according to consumer queries, encompassing factors such as product ratings, popularity (bestselling), and additional attributes. Conversely, Spotify does not reveal a song's popularity, whereas SoundCloud shows the number of times a song has been listened to. The choice of disclosing social influence information significantly impacts consumer responses and platform revenue, depending on whether the revenue model is based on product sales (e.g., Expedia and 7digital), subscriptions (e.g., Spotify Premium), or advertising (e.g., Pandora). These variations highlight the importance of considering both positions and social influence in platform strategy. See Figures A.12–A.16 in Web Appendix F.

[2] Although some previous research in search behavior has quantified the effect of product position in the e-commerce setting (Chen and Yao 2017, Ursu 2018), the effect of social influence has not been studied in this literature. On the other hand, the social influence literature has mainly investigated the impact of others' choices on an individual's decision making while ignoring the consumer search context (e.g., Cai et al. 2009, Ching 2010, Chen et al. 2011, Tucker and Zhang 2011, Zhang and Liu 2012). As far as we know, our study is the first to incorporate both position and social influence effects in a structural search model.

[3] Some recent works have also modeled consumer search in an equilibrium framework. For instance, Moraga-González et al. (2017) present a theoretical model to characterize how consumers' heterogeneous search costs affect firms' pricing policies in an equilibrium.

[4] The alternative approach to estimate these types of models is the GHK estimator (named after Geweke 1989, Keane 1994, Hajivassiliou and McFadden 1998). Note that we follow a similar approach as in Choi and Mela (2019) and Chung (2019), who allow for a stochastic element that enters search costs. Therefore, we use the logit-smoothed AR simulator for convenience. However, we explain in Web Appendix G that using an alternative modeling approach, the GHK estimator can be applied in estimating a search model as in Jiang et al. (2021).

[5] Figure 1 is extracted from Salganik (2008).

[6] Sun et al. (2019) investigate the normative effect of social influence on people's sampling behavior. For example, a person might listen to a well-known song because her friends also listen. In this scenario, social influence affects someone's behavior by conforming to the crowd's choice without getting new information about the chosen item. Because all 48 songs are unknown to our participants, social influence has an informative role in our case, in contrast to the normative effect.

[7] If songs have identical popularity (i.e., the same number of downloads), their positions are randomly determined among these similarly popular songs. For instance, see the second- and third-ranked songs in Figure A.9.

[8] These three experiments were conducted at different times and involved participants from different populations. We account for these variations by modeling individual behaviors and considering participants' characteristics.

[9] We also tested an alternative reading pattern where participants read each row from left to right before moving to the next row, yielding qualitatively similar results.

[10] Here, we follow the literature interpretation that the search cost is the clicking and scrolling costs for the list of items (Kim et al. 2010, Ursu 2018).

[11] The superscript "o" is provided as a mnemonic for "opened" or "observed."

[12] In other words, Weitzman (1979) finds the selection and stopping rules under the assumption $u(\vec{x}_s^o) = \max(\vec{x}_s^o)$.

[13] Note that the utility function $u(.)$ maps vectors of any length to real values. We state these sufficient conditions of $u(.)$ in Web Appendix A.

[14] This assumption is consistent with our data, where 98.9% of downloads happened right after these songs were sampled.

[15] See Olszewski and Weber (2015a) for the proof of their theorem 3. Olszewski and Weber (2015a, b) show that this selection and stopping rule is optimal under the specific model setting discussed here. We discuss some possible extensions in Web Appendix G.

[16] As a robustness check, we replace the exponential function with a quadratic function. Our main findings remain unchanged (see Web Appendix I).

[17] We consider different functional forms of increasing and concave functions for $u(.)$ such as log(.) and $\sqrt[3]{.}$. All results are consistent and qualitatively the same.

[18] Whereas we recognize the importance of allowing participants to update their presearch beliefs based on outcomes, we restrict them from considering the exploration value. In other words, we assume that participants are myopic in a correlated learning problem as in Erdem (1998) and Ching and Lim (2020). Nonetheless, we assume participants are forward looking in determining the optimal search and stopping rules, aligning with previous sequential search literature. Note that in the context of sequential search with correlated learning over boxes (as in this paper), fully rational exploration-exploitation trade-off learning is NP-hard, meaning it is computationally infeasible for participants to perfectly balance exploration and exploitation (Chawla et al. 2020). Even the optimal decision cannot be approximated in polynomial time (Chawla et al. 2023). Therefore, people can exhibit bounded rationality when facing an NP-hard learning process (Tehrani and Ching 2024).

[19] Both *appeal* and *popularity* variables are standardized by subtracting them from their mean and then dividing them by their standard deviation. This puts them on the same scale, making comparisons

and analyses more accurate. Importantly, the results remain robust and consistent even when using nonstandardized data.

[20] It is possible that when a consumer discovers a song from a new artist, they may like it so much that they want to download the whole album (e.g., an artist may try to tell a coherent story by a collection of songs from the same album, and hence, consumers' marginal utility of listening any one song increases when they also listen to other songs from the same album). That's one example of songs from the same album being complements.

[21] Note that even though the utility function is concave, our model has another channel that can lead to complementarity in demand: a positive postdownload feedback would make the presearch belief (p_{ijt}) about remaining songs more optimistic, which can lead to higher sampling rate and higher demand for remaining songs.

[22] We have restated theorem 3 of Olszewski and Weber (2015a) in Web Appendix A.

[23] More precisely, Salganik et al. (2006) show evidence that popularity information only matters in explaining the Gini coefficient of a song's success measured by the number of downloads, and they did not investigate the role of participants' search behavior, the song's position, and social influence on it.

[24] Our identification argument is similar to Ursu (2018), who also uses the random assortment to identify the cost function and position effect. Furthermore, this paper takes into account the effect of social influence on the search process.

[25] There are several prominent examples of the two-step estimation procedures, for example, Heckman selection models (Heckman 1979), the control-function approach for the robust estimation of nonlinear models with endogenous variables (Terza et al. 2008, Wooldridge 2014), and the dynamic stockpiling structural model (Hendel and Nevo 2006). Our approach also takes advantage of the existence of the Independent versus Social Influence groups to estimate the position and social influence in two distinctive stages to find unbiased causal effects.

[26] Beyond comparing point estimates, we also calculate the marginal effects to address the nonlinearity of the model. From our data, we consider a woman of average age with a dial-up connection. In the matrix display, the marginal effects of the first position in the one-step versus two-step models are similar, with values of 0.00010 versus 0.00012, respectively. However, these marginal effects are significantly different in the column format, with values of −7.28E-06 versus 0.0002. Furthermore, in the matrix display, the marginal effects of social influence in the one-step versus two-step models are also similar, with values of 0.00246 versus 0.00247, respectively. In contrast, these marginal effects are significantly different in the column format, with values of 0.008 versus 0.0048. These results are robust across different individual characteristics.

[27] Note that $w_{k+1} = u(k+1) - u(k)$ can be rewritten as $\mathbb{E}[u(\vec{x}_S^o \cup \{j\} | x_j = 1)] - u(k)$, which is the expected marginal utility of song j being high quality.

[28] Using a direct approximation of *SLL* by finding P_{iR_id} and the stepwise indicator function leads to two well-known issues in the estimating parameters: (i) a low finite number of draws can result in $\hat{P}_{iR_id} = 0$, and (ii) the simulated probabilities may lack smoothness because of the non–twice differentiable nature of the indicator function. Consequently, employing the first and second derivatives to optimize the SLL will not be feasible.

[29] Our results are consistent and qualitatively the same across other smoothing scaling parameters we tested, such as $\lambda = 1/5, 1/10, 1/25, 1/50, 1/100$. An alternative approach could involve using the GHK-estimator (Jiang et al. 2021), which does not rely on the choice of λ. Moraga-González et al. (2023) propose another way to estimate a structural search model by formulating the search problem as a discrete choice model.

[30] Details of counterfactual setting are reported in Web Appendices C and D.

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