

Personalization, Algorithmic Dependence, and Learning

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Abstract

Personalized recommendation systems are now an integral part of the digital ecosystem. However, users’ increased dependence on these personalized algorithms has heightened concerns among consumer protection advocates and regulators. In this work, we bring an information-theoretic perspective to this problem and examine the underpinnings of algorithmic dependence and its downstream implications for users’ preference learning and independent decision-making ability, an important construct given the growing fear of adversarial AI. We develop a utility framework where users consume experience goods and sequentially learn their preferences to examine the effect of personalized algorithms on the learning process. We theoretically establish regret bounds for different types of users based on their dependence on the personalized algorithm. Our theoretical results demonstrate the rationality of algorithmic dependence as the gain from following the personalized algorithm scales linearly with time periods. We then develop an empirical framework to obtain model-free measures of regret for different user types. We find that personalized algorithms generate significant welfare gains, but these gains come at the expense of users’ preference learning and independent decision-making. Finally, we demonstrate that simple policy interventions can help balance the trade-off between welfare and learning, offering insights for both platforms and users.

Keywords: personalized algorithms, recommendation system, preference learning, consumer protection, linear bandits, reinforcement learning

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1 Introduction

Personalized recommendation systems are now an integral part of the digital ecosystem. Digital platforms use massive amounts of consumer-level data to deliver personalized recommendations. One of the canonical examples of recommendation systems is the Netflix movie recommendation algorithm, which reportedly saves the company over one billion dollars annually by reducing the churn rate [Gomez-Uribe and Hunt, 2015]. Other examples include Facebook and Twitter’s news feed personalization, Amazon’s product recommendation, and YouTube’s video recommendation algorithm.

In today’s digital age, the online marketplace is saturated with many options, presenting users with the challenge of sifting through too many options to find what they truly want. Personalized recommendation systems have emerged as a solution to this problem with the intent to make users’ choices easier by reducing their search costs. These systems are designed to effectively narrow down options in real-time and guide users towards products or services that best align with their preferences and needs. By doing so, a personalized recommendation system ensures that users can select a fitting item without the need to explore the vast digital landscape exhaustively.

However, as the adoption and reliance on personalized recommendation systems grow, there are increasing concerns regarding users’ algorithmic dependence [Bućinca et al., 2021]. Prior research has shown the pitfalls of algorithmic dependence by documenting the users’ tendency even to take clearly incorrect recommendations [Spatharioti et al., 2023], risks to user well-being [Banker and Khetani, 2019], and inefficiencies in users’ decision-making [McLaughlin and Spiess, 2022]. Regarding the mechanism behind algorithmic dependence, prior work in economics and marketing has suggested the presence of time-inconsistent preferences [Allcott et al., 2022] and search costs [Korganbekova and Zuber, 2023]. However, little is known about the algorithm’s information advantage and how it feeds algorithmic dependence.

In this work, we bring an information-theoretic perspective to this problem and examine the underpinnings of algorithmic dependence and its downstream implications for users’ preference learning. In particular, we study digital contexts where users consume content sequentially and may have uncertainty about their preferences given the vast space of product features, which they resolve through experience. Personalized recommendations influence the process through which users learn their preferences by affecting the decisions they make. For example, a news reader interested in social justice topics may rarely explore other content if the algorithm correctly identifies her taste and only exposes her to this type of content.

Thus, dependence on algorithmic recommendations can have important implications for user learning.

Understanding algorithmic dependence and its downstream effects on users' learning is crucial from a consumer protection perspective, as users who heavily rely on algorithms without fully learning their preferences are more vulnerable to digital manipulation by adversarial AI, a topic of growing concern among policy-makers [Kusnezov et al., 2023]. In particular, when users lack a clear understanding of their own preferences, they make poorer decisions in the absence of recommendation systems, creating a feedback loop in which they become increasingly dependent on these systems while learning less about their own preferences. In this paper, we study the interplay between personalization, algorithmic dependence, and preference learning and aim to answer the following questions:

1. How does the algorithm's information advantage translate into better recommendations? Are there information-theoretical guarantees on the regret performance of personalized recommendation systems?
2. How does the dependence on a personalized algorithm affect user learning? How can we quantify the impact?
3. What consumer protection policies could generate good recommendations while helping users learn their preferences?

To answer these questions, we face several challenges. First, we need a theoretical framework that allows us to formally characterize the personalized algorithm's information advantages and disadvantages over individual users. In particular, we need our framework to capture learning by the algorithm and users separately from any given prior. Second, we need to theoretically compare the outcomes for users who follow personalized algorithms with those who do not. However, since algorithms and users operate under different conditions, the theoretical guarantees, such as regret bounds, often include parameters that make them inherently incomparable. Hence, we need to obtain comparable regret bounds that allow us to assess the rationality of algorithmic dependence. Third, we need an empirical framework to evaluate the performance of different algorithms without necessarily deploying those policies online. In particular, we want the evaluation process to be model-free so we do not need to rely on model-based outcome estimates.

To address our first set of challenges, we build a general linear utility framework where users have some preference parameters over the space of product features, and products have search and experience features, consistent with Nelson [1974]. To characterize users' learning,

we turn to the literature on Bayesian learning and model users who update the posterior distribution of their preference parameters [Ching et al., 2013]. For users’ decision-making, we use the Thompson Sampling approach as it incorporates users’ Bayesian learning and is behaviorally plausible [Schulz et al., 2019, Mauersberger, 2022]. Under Thompson Sampling algorithms, users sample from the posterior distribution of preferences to choose an item and update the posterior distribution according to their experience. We then characterize the personalized recommendation system and its decision-making process as a low-rank model that mimics the reality of personalized algorithms used by platforms and parsimoniously accounts for the platform’s information advantage over a single user who only has access to search features.

For the second challenge, we turn to the literature on bandits [Lattimore and Szepesvári, 2020]. In particular, given the role of information advantage in our study, we focus on the bandits literature that offers information-theoretic regret bounds for the performance of different adaptive learning algorithms Russo and Van Roy [2016]. To isolate the impact of recommendation systems on outcomes, we focus on two types of users: (1) self-exploring users who make decisions on their own as though there is no recommendation system, and (2) recommendation-system-dependent (RS-dependent henceforth) users who follow the recommendations provided by the recommendation system. We find that the regret for self-exploring users has a lower bound that scales linearly in time periods because self-exploring users can, at best, identify the first-best product based on the search features. Conversely, the RS-dependent user has an information-theoretic upper bound for regret that grows sub-linearly in time periods. Together, our theoretical findings suggest that the welfare gain from following the RS grows linearly in time periods, highlighting a mechanism for rational dependence, even absent the search costs and time-inconsistent preferences.

Third, to empirically examine the impact of personalized algorithms on both welfare and learning outcomes, we use MovieLens data, which is the main public data set used as a benchmark for personalized recommendation systems. To facilitate a model-free regret evaluation, we focus on a small sample of users who have provided many ratings so we can use their observed outcomes instead of estimating them from models. We then take a hold-out subset of size 20 from the movies they have rated and exclude it from the training part. This creates a subset of products for each user in the test set, which allows us to evaluate how different each model’s prescription is from the observed first-best in the set. Lastly, we embed a state-of-the-art matrix factorization algorithm to simulate a personalized algorithm that captures the reality of algorithms used by the platforms [Cortes, 2018b].

We apply our empirical framework to the MovieLens data and examine regret and learning outcomes. We first focus on the algorithm’s information advantage and welfare gains from following the algorithm. We find a significantly better regret performance by the personalized algorithm. Notably, even compared to the self-exploring user who knows her own preferences, the personalized algorithm has a persistent advantage. Further, our results show that the algorithm quickly surpasses the performance of the self-exploring user with known preferences, emphasizing its efficiency due to low-rank learning. This is an important empirical finding, as we do not impose any specific rank constraint that forces the problem to be low-rank. Together, the algorithm’s better long-run performance and faster learning rationalize algorithmic dependence, even absent search costs or time-inconsistent preferences.

Next, we focus on the implications of algorithmic dependence for learning. We first show that the absolute amount of preference learning is higher for self-exploring users than RS-dependent users when they start from an identical prior. Motivated by the trade-off between welfare and learning, we develop a new regret measure defined as *counterfactual regret*, which helps quantify the potential welfare consequences of insufficient learning. The counterfactual regret measures the expected regret incurred by a user in each period if they make decisions independently without the help of the personalized algorithm. As such, a user with insufficient learning would make worse decisions on their own. The key advantage of this measure is that it has the same unit as our main regret measure, which offers greater interpretability and facilitates joint optimization of welfare and learning outcomes. We compute counterfactual regret for RS-dependent users and show that while these users enjoy a low regret due to following personalized recommendations, they have a higher counterfactual regret than self-exploring users because they become worse independent decision-makers in the absence of personalized algorithms. Therefore, our examination of learning outcomes suggests that although personalized algorithms help users make better decisions that increase their welfare, these algorithms can act as a barrier to user learning since they algorithms can limit the organic exploration process users engage in.

An immediate question that arises, given the trade-off between welfare and learning, is whether there are policies that can balance the trade-off. We consider a simple class of policies whereby the recommendation system is probabilistically unavailable for a proportion of time periods. Notably, we find that there are policies in this class of policies that push the Pareto frontier of welfare and learning, find the right balance in the trade-off between these two outcomes, and achieve good outcomes in terms of both regret and counterfactual regret. Specifically, we find that with a small amount of randomization in the availability of

the algorithm, users will learn almost the same amount as the self-exploring user while only sacrificing a small amount of welfare. Our findings offer important implications for platforms and users who want to self-regulate.

In summary, our paper provides several contributions to the literature. Substantively, we present a comprehensive study of the effect of personalized recommendation systems on important welfare and learning outcomes through a series of theoretical and empirical analyses. We document that even when personalized algorithms enhance welfare by offering better product recommendations to users, they can negatively affect users’ learning by limiting the degree to which they explore their own preferences. While concerns related to privacy, fairness, and polarization are more thoroughly studied in the past literature on personalized recommendation systems, the topic of algorithmic dependence and its downstream impacts on users’ learning has been less studied. Thus, our work extends this policy debate by deriving the underpinnings of algorithmic dependence and highlighting its negative consequences for users’ independent decision-making ability, offering insights that are increasingly relevant given growing concerns about adversarial AI. Methodologically, we introduce a framework that allows us to establish theoretical regret bounds for users based on their dependence on the personalized algorithm. A key innovation of our approach is its ability to capture the information advantage of personalized algorithms through a low-rank assumption and access to experience features unavailable to users. Additionally, we develop a counterfactual regret measure that serves as a valuable benchmark for evaluating the effects of adversarial AI. Finally, from a policy standpoint, we find that there are exploration-based policies that are simple enough to be implemented and achieve desirable outcomes in terms of both welfare and learning.

2 Related Literature

First, our paper relates to the literature on personalization. Prior methodological work in this domain has offered a variety of methods to generate personalized policies, such as low-rank matrix factorization models for collaborative filtering and a host of causal machine learning methods [Linden et al., 2003, Mazumder et al., 2010, Athey and Imbens, 2019, Koren et al., 2021, Rafeian and Yoganarasimhan, 2023]. Related applied work in this domain has focused on different aspects of personalization, such as developing personalized algorithms tailored to specific problems [Hauser et al., 2009, Urban et al., 2014, Liberali and Ferecatu, 2022, Rafeian, 2023, Rafeian et al., 2023], the interplay between personalization and consumer protection policies [Goldfarb and Tucker, 2011, Johnson et al., 2020, Rafeian and Yoganarasimhan, 2021, Johnson et al., 2023, Bondi et al., 2023], and the tension between content homogenization

vs. content diversity as a result of personalization [Fleder and Hosanagar, 2009, Nguyen et al., 2014, Song et al., 2019, Holtz et al., 2020, Aridor et al., 2020, Anwar et al., 2024]. Our work extends this stream of work by bringing an information-theoretic view and focusing on the foundations of algorithmic dependence and its negative impact on users’ learning. In particular, we combine the insights from the literature on matrix factorization with bandits to establish theoretical regret bounds for users as a function of their dependence.

Second, our paper relates to the literature on consumer search and personalized rankings [Jeziorski and Segal, 2015, Ursu, 2018, Dzyabura and Hauser, 2019, Yoganarasimhan, 2020, Korganbekova and Zuber, 2023, Donnelly et al., 2024]. Most papers in this literature build a sequential search model akin to Weitzman [1979] to model consumers’ search behavior and estimate structural parameters such as search costs. Under this modeling framework, consumers do not learn their preferences through experience but realize the match value of each item upon a costly search. The exception is Dzyabura and Hauser [2019], which allows for learning, but that paper does not allow for experiential learning. A common theme in the stream of work on consumer search is that personalized algorithms create value by reducing consumers’ search costs. In that sense, search cost is the main driver behind algorithmic dependence. Our work differs from this stream of literature as we focus on a channel separate from search cost that drives algorithmic dependence: the algorithm’s information advantage. In particular, we characterize the personalized algorithm’s information advantage in the context of experience goods, which makes it a better predictor of whether the user likes the product or not than the users themselves.

Third, our paper relates to the literature on consumer learning. Understanding consumer learning dynamics has been of great interest to researchers in marketing [Roberts and Urban, 1988]. Ever since the seminal paper by Erdem and Keane [1996] who modeled forward-looking consumers who make decisions under uncertainty and engage in an exploration-exploitation trade-off, numerous studies have focused on choice contexts where dynamic learning plays an important role [Akerberg, 2003, Crawford and Shum, 2005, Erdem et al., 2005, Hitsch, 2006, Erdem et al., 2008, Ching et al., 2013]. An important issue in this stream of work is computational complexity, which has made its application infeasible in high-dimensional domains [Tehrani and Ching, 2023]. More recently, Lin et al. [2015] have shown that using heuristic-based index strategies for learning yields similar performance while having the advantage of computational and cognitive simplicity. We extend this stream of literature by offering a Thompson Sampling approach for characterizing consumer choice and learning process, which is another cognitively simple alternative to the typical dynamic programming

solution to the exploration-exploitation trade-off and has been shown to be a behavioral plausible framework to model consumer behavior [Schulz et al., 2019]. We further demonstrate how the increased flexibility offered by the Thompson Sampling approach can help researchers study settings with high-dimensional learning and establish information-theoretic regret bounds.

Fourth, our work relates to the vast literature on adaptive learning and multi-armed bandits. Prior research in this domain has offered a variety of algorithms to use [Lattimore and Szepesvári, 2020]. Although Thompson sampling has been around since the work by Thompson [1933], it has only recently gained traction after providing a remarkable empirical performance better than state-of-the-art benchmarks [Chapelle and Li, 2011]. Since then, many researchers have attempted to provide theoretical guarantees on Thompson sampling for a variety of adaptive learning problems [Agrawal and Goyal, 2012, 2013, Russo and Van Roy, 2014, 2016]. For a comprehensive review of Thompson sampling, please see Russo et al. [2018]. Most of the literature in this domain focuses on a single learner that optimizes the action and updates parameters upon experience. Our work extends this single-agent framework to a setting with both a learning recommendation system and an agent, offering new insights for modeling general principal-agent problems in contexts with decision-making under uncertainty. We offer theoretical regret bounds for different users based on their level of dependence on the algorithm.

3 Modeling Framework

We consider a general principal-agent model, where the principal is a platform that designs a Recommendation System (RS) that offers personalized product recommendations and the agent is a user of the platform who wants to consume products on the platform. The products available are experience products, meaning that only a subset of their features are available prior to consumption and some of their features are only realized after consumption [Nelson, 1974]. There are numerous examples of such contexts, including movie recommendations, news personalization, and content recommendation on social media apps. In this section, we first characterize the user’s utility model in §3.1 and then describe users’ preference learning in §3.2. In §3.3, we discuss the user’s choice in two different regimes with and without the personalized RS.

3.1 Users’ Utility Model

We propose a general utility framework in which user i derives utility from selecting action A_j from the action set \mathcal{A} . In this context, each action corresponds to consuming a distinct

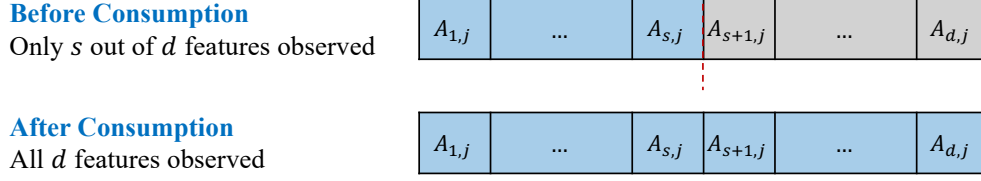


Figure 1: Illustration of search and experience features

experience product, represented by a d -dimensional set of attributes, i.e., $\mathcal{A} \subset \mathbb{R}^d$. Following the literature on experience goods [Nelson, 1974], we categorize the product features into two types: (1) *search features*, which are attributes known before consumption (e.g., a movie’s runtime, genre), and (2) *experience features*, which are realized only after consumption (e.g., the presence of a surprise ending). For convenience, we denote the first s features as search features and the remaining $d - s$ features as experience features. Figure 1 illustrates the distinction between these two feature types. We denote user i ’s utility from consuming product A_j by $u_i(A_j)$ and characterize it by a user-specific vector of preferences $\theta_i \in \mathbb{R}^d$ in a linear specification as follows:

$$u_i(A_j) = \theta_i^T A_j + \epsilon_{i,j}, \quad (1)$$

where $\epsilon_{i,j}$ is the error term, drawn from a normal distribution with mean zero and known variance σ_ϵ^2 . Although we assume linearity for theoretical simplicity, this assumption is not overly restrictive, as a rich set of features could be used to approximate user utility in a linear manner. To account for the distinction between search and experience features, we decompose utility as follows:

$$u_i(A_j) = \underbrace{\sum_{k=1}^s \theta_{i,k} A_{k,j}}_{\text{utility from search features}} + \underbrace{\sum_{l=s+1}^d \theta_{i,l} A_{l,j}}_{\text{utility from experience features}} + \epsilon_{i,j}, \quad (2)$$

where the utility from search features is the part available to the user prior to consumption, but the utility from the experience features is only realized after consumption.

3.2 Users’ Preference Learning

We extend our framework to sequential settings where users learn their preference parameters through sequential consumption of products. We take an information-theoretic perspective, recognizing that users may not have complete knowledge of their preference parameters and may experience uncertainty about them. This uncertainty is particularly likely in rich product

spaces, such as content recommendation domains [Yao et al., 2022]. In such settings, users resolve their uncertainty sequentially by consuming products and learning their preferences over time. For example, a movie viewer may be uncertain about their preference for a specific sub-genre or an new visual style and thus learns by watching multiple films within that category.

Let t denote each time period and $A_{i,t}$ the product chosen by user i in period t . For notation brevity, we define $U_{i,t} = u_i(A_{i,t})$ and let $\mathcal{H}_{i,t}$ denote the prior sequence of products (actions) and utility outcomes up until period t , that is, $\mathcal{H}_{i,t} = (A_{i,1}, U_{i,1}, A_{i,2}, U_{i,2}, \dots, A_{i,t}, U_{i,t})$. We assume θ_i is drawn from a Normal distribution $N(\mu_{i,0}, \Sigma_{i,0})$. The user starts with a prior $\tilde{\theta}_{i,0} \sim N(\mu_{i,0}, \Sigma_{i,0})$ and updates the preference parameters at the end of each time period t given the prior sequence $\mathcal{H}_{i,t}$ according to the following rule:

$$\mu_{i,t} = \mathbb{E}[\theta_i \mid \mathcal{H}_{i,t}] \quad (3)$$

$$\Sigma_{i,t} = \mathbb{E}[(\theta_i - \mu_{i,t})(\theta_i - \mu_{i,t})^T \mid \mathcal{H}_{i,t}] \quad (4)$$

It is important to note that the presence of uncertainty does not imply that users have entirely uninformative priors. For instance, a user may already have a reasonably well-calibrated belief about their enjoyment of a new visual style in movies. The sequential nature of learning indicates that users update their parameters in every time period in a Bayesian fashion. Following the literature on Bayesian learning [Ching et al., 2013, Peleg et al., 2022, Tehrani and Ching, 2023], for any $t \geq 0$, we present the user’s parameter updating from $\mu_{i,t}$ and $\Sigma_{i,t}$ to $\mu_{i,t+1}$ and $\Sigma_{i,t+1}$ as follows:

Algorithm 1 Bayesian Updating

Input: $\mu_{i,t}, \Sigma_{i,t}, A_{i,t}, U_{i,t}$

Output: $\mu_{i,t+1}, \Sigma_{i,t+1}$

- 1: $\Sigma_{i,t+1} \leftarrow \left(\Sigma_{i,t}^{-1} + \frac{1}{\sigma_\epsilon^2} A_{i,t} A_{i,t}^T \right)^{-1}$
 - 2: $\mu_{i,t+1} \leftarrow \Sigma_{i,t+1} \left(\Sigma_{i,t}^{-1} \mu_{i,t} + \frac{1}{\sigma_\epsilon^2} A_{i,t} U_{i,t} \right)$
-

Algorithm 1 determines user learning given any consumption sequence $\mathcal{H}_{i,t}$. See Appendix A for the analytical derivation of the updating rules. Our goal is to examine how different consumption sequences can result in different levels of learning.

3.3 User Choice

We now discuss the user’s decision-making process that determines the consumption sequence $\mathcal{H}_{i,t}$. To do so, we need to characterize the choice architecture in each period. For any product set $\mathcal{A} = \{A^{(1)}, A^{(2)}, \dots, A^{(K)}\}$, we consider the following choice architecture:

$$\underbrace{A^{(p)}}_{\text{recommended}}, \underbrace{A^{(1)}, A^{(2)}, \dots, A^{(K)}}_{\text{not recommended}},$$

where one product from the set is recommended and rest of the products are not recommended.¹

We now characterize the user’s decision-making process in the definition below:

Definition 1. *Let $\mathcal{I}_{i,t}$ denote all the information available to user i at time t . The user’s decision-making process is characterized by the policy $\pi(\cdot \mid \mathcal{I}_{i,t})$, which is a probability distribution over products conditional on the information and products available.*

To isolate the impact of personalized algorithms on users, we consider two types of users: (1) *self-exploring user*, who makes decisions on their own as though there is no personalized RS, and (2) *RS-dependent user* who follows the personalized recommendation in every time period. Both types have the same learning process as described in Algorithm 1. In what follows, we first characterize the self-exploring user’s choice in §3.3.1, and then present how the RS provides personalized recommendations to characterize the consumption sequence for the RS-dependent users in §3.3.2.

3.3.1 Self-Exploring User

In the absence of the personalized recommendation, users make decision on their own. Given the utility framework in Equation (1), a forward-looking utility-maximizing user wants to optimize the overall utility over T periods. This naturally motivates users to learn their preference parameters through experience and balance good decision-making with proper exploration of their own preference parameters. We can define the objective function for a forward-looking user as maximizing the discounted expected utility stream as follows:

$$\operatorname{argmax}_{\pi} \mathbb{E} \left[\sum_{t=0}^{\infty} \delta^t U_{i,t} \mid \mu_{i,0}, \Sigma_{i,0}, \pi \right], \quad (5)$$

where δ is the discount factor and the expectation is taken over the randomness in products $A_{i,t}$ and utilities $U_{i,t}$. Typical approaches to find the optimal sequence of choices by users

¹Having only one recommended action is only for simplicity and one could easily extend the framework to cases with multiple recommended actions.

involve solving a dynamic programming problem, which is known to be an NP-hard problem. The lack of cognitive simplicity of dynamic programming solutions has motivated researchers to study the simpler heuristic-based strategies as the underlying learning process [Lin et al., 2015, Tehrani and Ching, 2023].

We draw inspiration from this stream of literature and assume that users employ a Thompson Sampling approach that is a simple and intuitive heuristic-based strategy consistent with Bayesian learning [Thompson, 1933]. In addition, the prior literature has documented Thompson Sampling algorithm’s behavioral plausibility as a framework to model consumer choice and learning [Schulz et al., 2019, Mauersberger, 2022] and its excellent empirical performance in terms of welfare [Chapelle and Li, 2011].²

Thompson Sampling aims to find the right balance between exploration and exploitation in the decision-making process. The algorithm starts by initializing the user’s prior belief distribution about the preference weights $N(\mu_{i,0}, \Sigma_{i,0})$. It then draws $\tilde{\theta}_{i,0}$ from this distribution and computes the utility from search features for all possible products by plugging in $\tilde{\theta}_{i,0}$ for $\theta_{i,0}$ in Equation (2). It is important to note that the user cannot use experience features because those features are not available prior to consumption. In the next step, the algorithm chooses the product that maximizes the estimated utility and observes the utility $U_{i,0}$ for that instance. Finally, the algorithm applies Bayesian updating procedure in Algorithm 1 using the new instance and updates the posterior distribution of preference weights. The Thompson Sampling algorithm continues this process for \mathcal{T} periods.

Algorithm 2 Choice and Learning for the Self-Exploring User

Input: $\mu_{i,0}, \Sigma_{i,0}, \mathcal{A}, \mathcal{T}$
Output: $\mathcal{H}_{i,\mathcal{T}}, \{\mu_{i,t}, \Sigma_{i,t}\}_{t=1}^{\mathcal{T}}$

- 1: **for** $t = 0 \rightarrow \mathcal{T}$ **do**
- 2: $\tilde{\theta}_{i,t} \sim N(\mu_{i,t}, \Sigma_{i,t})$ ▷ Sampling preference weights
- 3: $A_{i,t} \leftarrow \operatorname{argmax}_{A_j \in \mathcal{A}} \sum_{k=1}^s \tilde{\theta}_{i,k,t}^T A_{k,j}$ ▷ Selecting action based on search features
- 4: $\Sigma_{i,t+1} \leftarrow \left(\Sigma_{i,t}^{-1} + \frac{1}{\sigma_\epsilon^2} A_{i,t} A_{i,t}^T \right)^{-1}$ ▷ Updating posterior variance
- 5: $\mu_{i,t+1} \leftarrow \Sigma_{i,t+1} \left(\Sigma_{i,t}^{-1} \mu_{i,t} + \frac{1}{\sigma_\epsilon^2} A_{i,t} U_{i,t} \right)$ ▷ Updating posterior mean
- 6: **end for**

Assuming that the self-exploring user uses Thompson Sampling has several key advantages. First, it is a commonly used heuristic strategy for this dynamic problem, and early literature has shown it to be nearly optimal [Chapelle and Li, 2011]. Second, it is computationally

²The prior literature has documented lower regret for Thompson Sampling compared to the alternatives across several empirical domains.

light, making it advantageous in our later empirical analysis using the MovieLens data set.³ Third, due to its simplicity, it is easy to incorporate it in cases where there is a recommendation system present in the problem. We discuss this issue in the following section.

3.3.2 RS-Dependent User

We now focus on the user’s choice in the presence of the recommendation system. To do so, we first introduce a personalized RS that aims to simplify the user’s decision-making problem. Since we want to quantify the impact of the personalized RS on user-specific outcomes, we assume that the recommendation system’s objective is the same as that of user.⁴ A natural difference between the personalized RS and a single user is the fact that the system has access to the data of all other users. To understand how the recommendation system’s data advantage manifests itself in better decision-making capabilities, we first introduce some notations. Let $\Theta_{[d \times N]}$ denote the matrix of preference weights for a group of N users, i.e., $\Theta_{[d \times N]} = [\theta_1 \mid \theta_2 \mid \dots \mid \theta_N]$. In all major platforms, N is a very large number. Similarly, let $A_{[d \times J]}$ denote the matrix of attributes for all J products ($J = |\mathcal{A}|$) where each column represents the vector of attributes for a product. We can define the matrix analog of the user’s utility in Equation 1 as follows:

$$U = \Theta^T A + E, \quad (6)$$

where $U_{N \times J}$ represent the utility for each pair of user and product and $E_{N \times J}$ is a matrix of i.i.d error term drawn from a mean-zero Normal distribution with variance σ_ϵ^2 . The recommendation system has access to $U_{N \times J}^{\text{obs}}$, which is an incomplete realization of matrix U as each user reveals utility for a subset of items. The main question is how the data from other users $U_{N \times J}^{\text{obs}}$ help the personalized algorithm learn about the new user i with vector of preferences θ_i .

In principle, if the prior data from users do not inform us about the new user, the recommendation system’s strategy will be the same as the self-exploring user, presumably with a less informed prior because users know more about their own preferences than the RS. However, the prior empirical work on personalized recommendation systems suggests

³As a robustness check, we show that our qualitative insights will not change if we use an approximate dynamic programming solution to this problem.

⁴It is worth emphasizing that the only reason we make this assumption is to ensure that the impact of the recommendation system is not driven by the misalignment in objectives. It is generally easy to show that in cases where the objectives are misaligned, the extent of harm by the recommendation system will be larger [Kleinberg et al., 2022]. In that sense, our results will provide a lower bound for the negative impact caused by the RS.

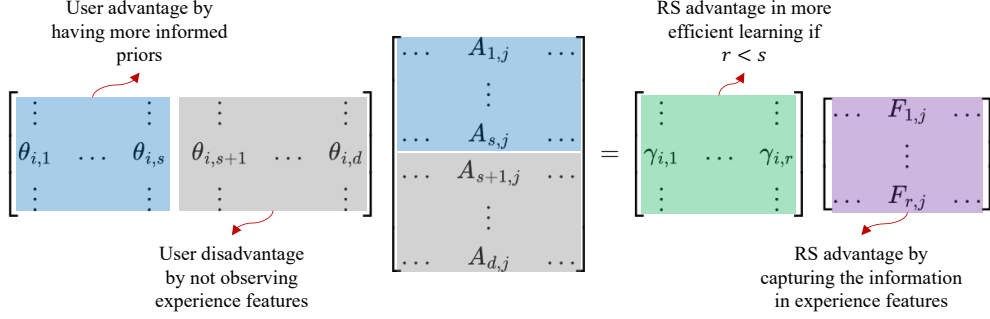


Figure 2: Comparison of information advantage by the RS and users

otherwise as it documents extensive similarities in user preferences [Koren et al., 2021]. The most common approach to characterize the similarities in user preferences is to use a factor model, which suggests that the matrix $\Theta^T A$ can be factorized into two low-rank matrices. In particular, we make the following low-rank assumption:

Assumption 1. *The expected utility matrix $\Theta^T A$ can be decomposed as follows:*

$$\Theta_{[d \times N]}^T A_{[d \times J]} = \Gamma_{[r \times N]}^T F_{[r \times J]}, \quad (7)$$

where $F_{[r \times J]} = [F_1 \mid F_2 \mid \dots \mid F_J]$ is the matrix of product-specific factors for all J products, and $\Gamma_{[r \times N]} = [\gamma_1 \mid \gamma_2 \mid \dots \mid \gamma_N]$ presents the matrix of user-specific factor weights for all N users.

We can now view the recommendation system's data advantage in light of Assumption 1. Because the recommendation system has other users' prior data, it has access to an accurate estimate of the product-specific matrix F , which captures not only search features, but also experience features. As such, the recommendation system's task of learning user i 's preference parameters will turn into the task of learning user i 's weights for r -dimensional products because we have: $\theta_i^T A_j = \gamma_i^T F_j$. Hence, the recommendation system's data advantage manifests in two ways: (1) learning r -dimensional weights as opposed to the self-exploring user's learning of d parameters, and (2) access to a low-rank embedding of product space that contains both search and experience features. Figure 2 compares the information advantage of the RS and users, emphasizing the potential for users to have more informed priors. These insights are essential for establishing theoretical guarantees for different algorithms.

We now present the procedure that determines choice and learning for the RS-dependent user in Algorithm 3. In this setting, not only is there a user who learns her preference parameters through experience, there is also a recommendation system that learns user

preferences and offers recommendations. Both players learn user i 's preference parameters, but they operate in different spaces: user i learns her own parameters θ_i in the d -dimensional space, whereas the recommendation system learns user i 's preference weights for factors in the r -dimensional space. To distinguish between these two learning processes, we use superscripts (θ) and (γ) to refer to the parameters of both players' prior distributions: $\mu_{i,0}^{(\theta)}$, $\Sigma_{i,0}^{(\theta)}$, $\mu_{i,0}^{(\gamma)}$, and $\Sigma_{i,0}^{(\gamma)}$.

The RS moves first in each time period. Since the recommendation system has access to F , it only wants to learn γ_i . As such, it engages in a Linear-Gaussian Thompson Sampling procedure, where it first draws $\tilde{\gamma}_{i,t}$ from the posterior distribution and then recommends the product with the highest expected utility (lines 2 and 3). The RS-dependent user always follows the recommended action (line 4). Once the utility is realized, both the user and recommendation system update parameters of their posterior distribution $\mu_{i,t+1}^{(\theta)}$, $\Sigma_{i,t+1}^{(\theta)}$, $\mu_{i,t+1}^{(\gamma)}$, and $\Sigma_{i,t+1}^{(\gamma)}$. The algorithm repeats this process for \mathcal{T} periods.

Algorithm 3 Choice and Learning for the RS-Dependent User

Input: $\mu_{i,0}^{(\theta)}, \Sigma_{i,0}^{(\theta)}, \mu_{i,0}^{(\gamma)}, \Sigma_{i,0}^{(\gamma)}, F, \mathcal{A}, \mathcal{T}$
Output: $\mathcal{H}_{i,\mathcal{T}}, \{\mu_{i,t}^{(\theta)}, \Sigma_{i,t}^{(\theta)}\}_{t=1}^{\mathcal{T}}, \{\mu_{i,t}^{(\gamma)}, \Sigma_{i,t}^{(\gamma)}\}_{t=1}^{\mathcal{T}}$

- 1: **for** $t = 0 \rightarrow \mathcal{T}$ **do**
- 2: $\tilde{\gamma}_{i,t} \sim N(\mu_{i,t}^{(\gamma)}, \Sigma_{i,t}^{(\gamma)})$ ▷ RS: Sampling low-dimensional weights
- 3: $A_{i,t}^{\text{RS}} \leftarrow \arg\max_{A_j \in \mathcal{A}} \sum_{k=1}^r \tilde{\gamma}_{i,k,t} F_k(A_j)$ ▷ RS: Selecting recommendation
- 4: $A_{i,t} \leftarrow A_{i,t}^{\text{RS}}$ ▷ User: Following recommendation
- 5: $\Sigma_{i,t+1}^{(\theta)} \leftarrow \left(\left(\Sigma_{i,t}^{(\theta)} \right)^{-1} + \frac{1}{\sigma_\epsilon^2} A_{i,t} A_{i,t}^T \right)^{-1}$ ▷ User: Updating posterior variance
- 6: $\mu_{i,t+1}^{(\theta)} \leftarrow \Sigma_{i,t+1}^{(\theta)} \left(\left(\Sigma_{i,t}^{(\theta)} \right)^{-1} \mu_{i,t}^{(\theta)} + \frac{1}{\sigma_\epsilon^2} A_{i,t} U_{i,t} \right)$ ▷ User: Updating posterior mean
- 7: $\Sigma_{i,t+1}^{(\gamma)} \leftarrow \left(\left(\Sigma_{i,t}^{(\gamma)} \right)^{-1} + \frac{1}{\sigma_\epsilon^2} A_{i,t} A_{i,t}^T \right)^{-1}$ ▷ RS: Updating posterior variance
- 8: $\mu_{i,t+1}^{(\gamma)} \leftarrow \Sigma_{i,t+1}^{(\gamma)} \left(\left(\Sigma_{i,t}^{(\gamma)} \right)^{-1} \mu_{i,t}^{(\gamma)} + \frac{1}{\sigma_\epsilon^2} A_{i,t} U_{i,t} \right)$ ▷ RS: Updating posterior mean
- 9: **end for**

A few points are worth noting about the RS-dependent user. First, we assume that the user follows the recommended product every time period. It is easy to rationalize this choice in a variety of ways due to the search cost associated with exploration. In the main analysis, we abstract away from this possibility and simply assume that the user always follows the recommendation system to illustrate the differences between the self-exploring

and RS-dependent users.⁵ Second, the user learning procedure in Algorithm 3 is identical to Algorithm 2, and the difference in learning only comes from the prior consumption sequence in these two settings. Finally, an implicit assumption we make here is that the RS-dependent user cannot learn from the recommendations beyond their own experience. This assumption is reasonable as recommendation systems are often very complex and it is not realistic to assume that users can learn further by observing that a product is recommended.

4 Theoretical Analysis

In this section, we theoretically examine the algorithms described earlier. We begin by defining our primary outcomes of interest in §4.1. Next, in §4.2, we establish regret bounds for both user types and examine the rationality of user dependence on the RS. Finally, in §4.3, we provide a general discussion of our findings and identify key empirical questions that warrant further investigation.

4.1 Main Outcomes

As discussed earlier, we are interested in two key outcomes: user welfare and user learning. In this section, we define these two key outcomes and formally present the measures we use for them. We can define user welfare for user i for T periods as the total sum of utility from actions chosen under policy π as follows:

$$\text{Welfare}_i(T; \pi) = \mathbb{E} \left[\sum_{t=0}^T u_i(A_{i,t}) \right], \quad (8)$$

where Welfare_i is a user-specific function that depends on user i 's preference parameters θ_i .⁶ Another closely tied measure that is often studied in the literature on sequential decision-making and linear bandits is *expected regret*, which takes the difference between the utility from some notion of first-best in each period and user welfare. We formally define *expected regret* as follows:

Definition 2. Suppose that $A_i^* \in \arg\max_{a \in \mathcal{A}} \mathbb{E}[u_i(a) \mid \theta_i]$ is the optimal action (product) given θ_i . For the sequence of actions $\{A_{i,t}\}_{t=0}^T$ chosen according to policy π , the **expected**

⁵If the RS-dependent user is rational and incurs a search cost when searching independently but no search cost when relying on the RS, then she faces a choice between searching on her own and following the RS every period. This dynamic decision process is complex, so we abstract away in the theoretical discussion.

⁶It is worth noting that we set the discount δ to zero as we consider a finite horizon problem.

regret is given as follows:

$$\text{Regret}_i(T; \pi) = \mathbb{E} \left[\sum_{t=0}^T (u_i(A_i^*) - u_i(A_{i,t})) \right], \quad (9)$$

where the expectation is taken over the randomness in the actions, utilities, and the prior distribution over θ_i .

This notion of expected regret is often referred to as the Bayes regret or Bayes risk. Consistent with the prior bandits literature, one advantage of using regret instead of welfare is the possibility of obtaining statistical bounds. We later use these bounds to conduct a theoretical analysis of our problem.

The second outcome we are interested in is user learning. Intuitively, the greater uncertainty the user has over her own preference parameters, the lower the degree of learning by the user. As such, we turn to the well-established concept of Shannon entropy that measures the amount of uncertainty or surprise in random variables [Shannon, 1948].

Definition 3. Let $A_{i,t}^*$ denote the random variable corresponding to the optimal action (product) given the prior sequence $\mathcal{H}_{i,t-1}$. We measure user's preference learning based on the **Shannon entropy** of $A_{i,t}^*$, which is defined as follows:

$$H(A_{i,t}^*) = - \sum_{k=1}^{|\mathcal{A}|} P(A_i^* = A_k \mid \mathcal{H}_{i,t-1}) \log_2 (P(A_i^* = A_k \mid \mathcal{H}_{i,t-1})). \quad (10)$$

According to this definition, a higher entropy means that the user is more uncertain as to what the optimal action is. For example, if the user deterministically chooses one action (maximum certainty and learning), the Shannon entropy of the optimal action will be equal to zero, i.e., $H(A_{i,t}) = 0$. On the other hand, when the user is maximally uncertain between actions, each action has an equal probability, and the Shannon entropy of optimal action will take its maximum value $H(A_{i,t}) = \log(|\mathcal{A}|)$.

A key challenge in using Shannon entropy as the primary measure of learning is that it is not directly comparable to regret, which serves as the main measure of welfare. To address this, we introduce the concept of *counterfactual regret*—the regret a user would incur at any given time period if they were to make decisions independently, without the influence of the personalized recommendation system. This measure allows us to capture the trade-off between welfare and learning: if lower regret actions come at the expense of user learning,

we expect counterfactual regret to be high for that user. We formally define the *expected counterfactual regret* as follows:

Definition 4. Let $\tilde{A}_{i,t}$ denote the counterfactual action (product), which is the random variable corresponding to the optimal action (product) given the prior sequence $\mathcal{H}_{i,t-1}$. This is the optimal action the user would choose based on her past learning through experience if the personalized algorithm was not available at period t only. For the sequence of counterfactual actions $\{\tilde{A}_{i,t}\}_{t=0}^T$ that would have been chosen in each period under π in the absence of RS, the expected **counterfactual regret** is given as follows:

$$\text{CounterfactualRegret} = \mathbb{E} \left[\sum_{t=0}^T \left(u_i(A_i^*) - u_i(\tilde{A}_{i,t}) \right) \right], \quad (11)$$

where the expectation is taken over the randomness in the actions, utilities, and the prior distribution over θ_i .

The main benefit of using the notion of *counterfactual regret* is its direct comparability with the actual *regret*. In cases where users follow the personalized algorithms to choose the product, we expect the counterfactual product they would choose without the personalized algorithm to be different from the one offered by the algorithm. As such, there will be a discrepancy between the *counterfactual regret* and the actual *regret*. The gap between the two highlights the potential welfare loss due to RS-dependence.

4.2 Regret Bounds

We now conduct a welfare analysis of the two types of users we defined earlier and establish theoretical regret bounds for their performance. We first present the regret bounds for self-exploring users who follow Algorithm 2 in §4.2.1. We then present the regret bounds for RS-dependent users who follow Algorithm 3 in §4.2.2. Finally, in §4.2.3, we theoretically compare the two regret bounds and examine the possibility of rational dependence.

4.2.1 Self-Exploring Users

We start by deriving the regret bounds for the self-exploring user. As shown in Algorithm 2, the user starts with a prior distribution $N(\mu_{i,0}, \sigma_{i,0})$ and samples from the prior to select the product and then updates the posterior distribution based on the realized utility. The user repeats the procedure until convergence to the first-best action (product), which is the best product identifiable by the user. We denote the first-best for self-exploring user by $A_i^{*,s}$ and define it as the product with the highest utility from *search* features if the preference

parameters are known, that is, $A_i^{*,s} \in \operatorname{argmax}_{A_j \in \mathcal{A}} \sum_{k=1}^s \theta_{i,k} A_{k,j}$. As such, the first-best identifiable by the self-exploring user is different from the first-best A_i^* in the regret equation (Definition 2), which allows us to write the following decomposition:

$$\begin{aligned} \operatorname{Regret}_i(T; \pi) &= \mathbb{E} \left[\sum_{t=0}^T (u_i(A_i^*) - u_i(A_{i,t})) \right] \\ &= \mathbb{E} \left[\sum_{t=0}^T (u_i(A_i^*) - u_i(A_i^{*,s})) \right] + \mathbb{E} \left[\sum_{t=0}^T (u_i(A_i^{*,s}) - u_i(A_{i,t})) \right] \end{aligned} \quad (12)$$

where the first element in the equation above is a summation over a constant gap between the expected utility from the two first-bests, and the second term is another notion of regret for the self-exploring user. Specifically, we can show that the second term is the same as the linear bandit regret with a s -dimensional vector of preference weights, which has existing information-theoretic regret bounds [Russo and Van Roy, 2016]. We use this insight to arrive at the following proposition:

Proposition 1. *Let π_{SE} denote the policy for the self-exploring user who follows the Thompson Sampling algorithm for choice and learning as in Algorithm 2. Further, let g denote the gap in expected utility between the first-best and the first-best based on only search features, that is, $g = \mathbb{E}[u_i(A_i^*) - u_i(A_i^{*,s})]$. The regret bound for this user is as follows:*

$$gT \leq \operatorname{Regret}_i(T; \pi_{SE}) \leq gT + \sqrt{\frac{H(A_{i,0}^*)sT}{2}}, \quad (13)$$

where $H(A_{i,0}^*)$ is the Shannon entropy of the prior distribution of optimal action for self-exploring user, defined at period 0, and s is the dimensionality of the search features.

As shown in this proposition, both lower and upper bounds contain a term linear in T . The upper bound further includes an information-theoretic bound, which is identical to the one established in Russo and Van Roy [2016]. The lower bound happens in the event where the user has no uncertainty about the preferences (i.e., $H(A_{i,0}^*) = 0$).

Next, we examine the gap g , which is defined as the difference between the first-best and the first-best based on only search features. Since this gap appears in the regret lower bound, it is crucial to understand how large of a magnitude it has and the theoretical conditions under which this term converges to zero. To do so, we need to introduce new notations: let $U_{i,j}^s$ and $U_{i,j}^x$ denote the utility the user derives from the search features and experience features, respectively. We can write the following proposition to characterize the lower bound

for the gap g :

Proposition 2. *Suppose that the search utility and experience utility across products are Normally distributed, such that $U_{i,j}^s \sim N(\mu_{i,s}, \sigma_{i,s})$ and $U_{i,j}^x \sim N(\mu_{i,x}, \sigma_{i,x})$. If search utility and experience utility are independent across products, the expected gap between the first-best and first-best based on the search features has the following lower bound:*

$$\mathbb{E}[u_i(A_i^*) - u_i(A_i^{*,s})] \geq \left(\sqrt{\sigma_{i,s}^2 + \sigma_{i,x}^2} - \sigma_{i,s} \right) \sqrt{2 \log(|\mathcal{A}|)} - O\left(\frac{\sqrt{\sigma_{i,s}^2 + \sigma_{i,x}^2} - \sigma_{i,s}}{\sqrt{\log(|\mathcal{A}|)}} \right) \quad (14)$$

As shown in Proposition 2, the gap depends on the variance of the utility from experience features and the number of products available. Therefore, the gap grows as the experience features play a larger role in determining a user's utility.

4.2.2 RS-Dependent Users

We now turn to establishing regret bounds for the RS-dependent user. The regret analysis for RS-dependent users is a bit more subtle. In this case, the user follows the recommendation from the personalized RS. As such, we need to find the regret bound for the RS. One could view the RS-dependent algorithm as a Thompson Sampling algorithm that operates in an r -dimensional environment, as it has access to the factor information. Under Assumption 1, the first-best that the RS could obtain is the same as the first-best in Definition 2. Therefore, the proposition below characterizes the following regret bound for the RS-dependent user:

Proposition 3. *Let π_{RS} denote the policy for the RS-dependent user who consistently follows the personalized recommendations. Further, let $H(A_{i,0}^{RS})$ denote the Shannon entropy of the prior distribution of optimal action for the personalized RS. The regret bound for the personalized RS is as follows:*

$$\text{Regret}(T; \pi_{RS}) \leq \sqrt{\frac{H(A_{i,0}^{RS})rT}{2}}, \quad (15)$$

where r is the number of factors. The expected regret for the RS-dependent user is equal to the expected regret for the personalized RS.

As shown in Proposition 3, the regret bound for the RS-dependent user does not depend on the dimensionality of the feature space but on the rank r . In many practical settings, r is much smaller than the dimensionality of the feature space (d) or search features (s) [Udell

and Townsend, 2019]. On the other hand, the main challenge for the RS is the initial lack of information about user preferences. In the extreme case, one could assume that the algorithm has an uninformative prior such that the prior distribution of optimal action gives all actions the same probability, which makes the Shannon entropy of the prior distribution of optimal action equal to $\log(|\mathcal{A}|)$. However, modern RS algorithms try to overcome the cold-start problem by better exploring the side information about the user [Farias and Li, 2019]. Thus, it is realistic to assume RS algorithms have a prior better than a random guess.

4.2.3 Regret Comparison and the Possibility of Rational Dependence

As highlighted earlier, both the user and the RS have some information advantages. The regret bounds in Propositions 1 and 3 illustrate their dependence on factors associated with each type of information advantage and disadvantage, as depicted in Figure 2. On the one hand, the platform’s algorithm benefits from access to data from other users, enabling it to efficiently identify the actual first-best by reducing the problem’s dimensionality from d to r , in contrast to the self-exploring user, who can only determine the first-best based on search features. On the other hand, in certain scenarios, users may have greater knowledge of their own parameters than the algorithm, resulting in a very small Shannon entropy of the prior distribution of the optimal action ($H(A_{i,0}^*) \approx 0$), which is substantially lower than that of the RS-dependent user ($H(A_{i,0}^*) \ll H(A_{i,0}^{RS})$).

Our goal in this section is to compare the regret bounds for self-exploring and RS-dependent algorithms established earlier. Combining the lower bound for the self-exploring user’s regret with the upper bound for the RS-dependent user’s regret, we arrive at the following corollary:

Corollary 1. *The difference in regret between self-exploring users and RS-dependent users has a lower bound given by:*

$$\mathbf{Regret}(T; \pi_{SE}) - \mathbf{Regret}(T; \pi_{RS}) \geq gT - \sqrt{\frac{H(A_{i,0}^{RS})rT}{2}} \quad (16)$$

A few key insights emerge from Corollary 1. First, the difference in Equation (16) directly corresponds to the welfare gain from following the RS, as the first-best terms in both regret values cancel out. Second, we observe that the positive term grows linearly in T , while the negative term grows sub-linearly. This implies that with a nonzero gap g , the welfare gain from following the RS increases linearly over time. Finally, the bound in Corollary 1 highlights that even in the absence of search costs and with time-consistent preferences, users will rationally

develop a dependence on the recommendation system (RS). This is particularly notable because our dependence results stem solely from the algorithm’s information advantage rather than time-inconsistent preferences or search costs—factors that have been central to prior explanations in the literature [Allcott et al., 2022, Korganbekova and Zuber, 2023].

4.3 Discussion

In this section, we provide a broader discussion and identify key empirical questions that warrant further investigation. As established in Corollary 1, the welfare benefits of RS tend to outweigh its downsides as the number of periods T increases. However, in real-world settings, users do not engage with the system for an infinite number of periods. As a result, self-exploring users may achieve better welfare outcomes within finite periods in cases where (1) when the gap g is small, and/or (2) when the RS initially provides poor recommendations and requires time to stabilize. The latter scenario is more likely if the effective rank r is high or if the RS starts with an uninformative prior. Therefore, assessing the net welfare impact of RS dependence in finite samples remains an empirical question, contingent on the actual values of g and r .

Second, another key outcome of interest in our study is learning. In particular, we want to know how following RS influences users’ preference learning and independent decision-making ability, measured by *counterfactual regret*. In principle, if the personalized recommendations create enough variation in products to learn preference parameters, we do not expect it to affect user learning. We know that the algorithm needs to explore in the beginning, which naturally creates some variation in product features consumed. However, comparing the upper bounds in Propositions 1 and 3, we know that the RS scales the regret in the order of $\sqrt{r/s}$ -fraction of the self-exploring user if they start from the same prior, that is, $H(A_{i,0}^*) = H(A_{i,0}^{\text{RS}})$. As such, the RS algorithm is likely to reach the exploitation stage quickly, potentially limiting the extent of exploration necessary for effective user learning. Specifically, if the exploitation phase primarily recommends a narrow set of products, users may experience insufficient variation to fully refine their preferences. Importantly, whether or not the exploitation stage of the algorithm generates enough variation for user learning largely depends on the distribution of user preferences and, therefore, is an empirical question. In our empirical framework, we evaluate the amount of learning and counterfactual regret for both self-exploring and RS-dependent users.

5 Empirical Framework

Motivated by the discussion outlined in §4.3, we now turn to our empirical framework to examine the finite-sample properties of self-exploring and RS-dependent algorithms in terms of both welfare and learning. In particular, we aim to develop an empirical framework to quantify the RS algorithm’s information advantage, which serves as a key driver of RS dependence. Additionally, we seek to examine the learning implications of this dependence and explore potential policies that can balance the trade-off between welfare and learning.

To accomplish these objectives, we require an empirical setting that meets the following criteria: (1) availability of preference data on user-product pairs, (2) access to a rich set of search features for products that allow us to estimate user preferences and simulate different learning patterns under various algorithms, and (3) the ability to integrate a state-of-the-art personalized recommendation system capable of learning complex user preferences and providing relevant recommendations.

To meet these three criteria, we utilize the MovieLens 1M dataset.⁷ The MovieLens dataset includes over one million user ratings from 6,040 distinct users on 3,706 unique movies, which serve as our measure of user preferences. Beyond ratings, the dataset provides detailed information about the movies, including genres, themes, and an extensive collection of tags associated with each movie, which we leverage as the set of search features. Lastly, the MovieLens dataset has been widely used as a benchmark for research on personalized recommendation systems, ensuring that we can integrate state-of-the-art recommendation algorithms into our empirical framework.

In this section, we begin by outlining our empirical strategy in §5.1. We then analyze the welfare gains derived from the personalized RS due to its information advantage in §5.2. Next, in §5.3, we investigate the learning outcomes for self-exploring and RS-dependent users. Finally, in §5.4, we explore the policy implications and identify potential strategies that balance the trade-off between welfare and learning objectives.

5.1 Empirical Strategy

In order to satisfactorily answer the empirical questions, we face several challenges. Before discussing these challenges in great detail, we need to state a few assumptions upfront. The first assumption we make is about the relationship between ratings and user utility. While our theoretical framework uses the concept of user utility, we only observe user ratings. Let

⁷This dataset is publicly available and can be accessed at <https://grouplens.org/datasets/movielens/1m/>.

$Y_{[N \times J]}$ denote the rating matrix for N users and J movies. We present our assumption that links ratings to utility as follows:

Assumption 2. *User i 's utility from watching movie j is well-approximated by user ratings, i.e., $U_{[N \times J]} \approx Y_{[N \times J]}$.*

Our next assumption pertains to the set of available search features. Since our data contain detailed movie tags in our data, we use these tags as the primary search features for each movie. These tags include attributes such as originality, great ending, and good soundtrack—features that are visible to users before consumption, as they appear in the movie profile on the website (for a complete list of movie tags, see Appendix B). Naturally, one could use all tags to characterize the dimensionality of user preferences. However, it is reasonable to assume that only a subset of these tags are important for user utility. Specifically, we assume that the top k most frequently used tags capture the search features. In our analysis, we set $k = 50$ and formalize this assumption as follows:

Assumption 3. *The matrix of movie's search features is defined as $A_{[51 \times J]} = [A_1 \mid A_2 \mid \cdots \mid A_J]$, where A_j represents features of movie j in terms of the aggregated rating and top 50 tags selected from the data.*

The final assumption we make is about the stability of true user preferences. As before, we let $\Theta_{[d \times N]}$ denote the user preferences for all N users. Our assumption about stable preferences is presented as follows:

Assumption 4. *For any user i , the true user vector of preferences is represented as θ_i for all time periods, independent of the movies watched.*

It is important to note that, in our setting, the user still learns their preferences through experience. While the actual preferences remain stable, the user's belief about these preferences can evolve over time. With all the assumptions clearly defined, we discuss these challenges along with their corresponding empirical strategy in the following sections.

5.1.1 Data Sparsity

For each user in our data, we only observe ratings for a subset of products, which makes it challenging to estimate user-level parameters θ_i . To overcome this challenge, we select a test sample of 100 users who have rated over 420 movies. Having a rich set of ratings for a user allows us to estimate parameters at the individual-level, by simply regressing the outcomes on movie features. As stated in Assumption 3, we use 51 features in our analysis that contain

search features that users could see on the TMDB website, including the aggregated rating for each movie as well as 50 other tag information.⁸

5.1.2 Model-free Regret Measurement

Empirically measuring regret for algorithms different from the one used in the data is fundamentally challenging. One approach is to impute ratings for unrated movies, but this requires highly accurate model-based estimates and risks information leakage between the imputation model and the algorithms being evaluated. Alternatively, restricting analysis to the set of movies each user has already rated avoids this issue but limits the ability of algorithms to identify strong recommendations outside the observed choices. Moreover, the movie recommendation setting differs slightly from the theoretical framework, where the action set \mathcal{A} is fixed. In reality, once content is consumed, users may not derive the same utility from repeated consumption. This makes the set of available products for each policy different, making an apples-to-apples comparison between algorithms impossible.

To address these challenges, we randomly select a hold-out set of 20 movies for each user in our test set, ensuring that these movies have been rated by the user so that we have access to the actual outcomes and the first-best option among them. We then exclude these 20 movies from the user’s training set, preventing the algorithm from accessing any information about the user’s ratings for these movies. Notably, while the hold-out set remains fixed for each user, it varies across users in our test data. This setup allows us to train any algorithm without the 20 hold-out movies and evaluate its regret and counterfactual regret in a model-free manner by directly using the user’s observed ratings for these hold-out movies.

5.1.3 Embedding the Personalized RS

To evaluate outcomes for RS-dependent users, we require a personalized RS that continuously updates its recommendations as it acquires more information about each user. As such, this has to be a personalized RS that can handle the cold-start problem. For each user i in the test set, we use the existing data of 5040 other users in the training set and combine it with the information about user i available at the beginning of each time period t . Following Cortes [2018a], we use a matrix factorization algorithm for our personalized recommendation system, which is widely used in the industry. We then train this recommendation system and predict ratings for a hold-out set of 20 movies. Based on these predictions, the RS recommends the movie with the highest predicted rating, which the RS-dependent user subsequently

⁸We only use 50 features to facilitate the OLS estimation of parameters at the user level. As a robustness check, we extend this to a richer set of features and more advanced learning algorithms. The qualitative insights remain unchanged.

consumes.

5.2 Algorithm’s Information Advantage and Regret Performance

We now turn to examining the algorithm’s information advantage and the welfare gains from following the RS. This empirical analysis complements the theoretical results from §4.2 by using real data to assess the finite-sample performance of different algorithms. Specifically, we aim to address two key questions: (1) how quickly the RS learns to make high-quality recommendations on the hold-out set of 20 movies and (2) whether these recommendations outperform those that users could identify based on observable search features. The first question pertains to the efficiency of low-dimensional learning through the factor model, while the second captures the inherent gap g —the difference between the first-best option identified by the RS and the best choice the user could make based on the search features.

For each user in our test set, we use the actual sequence of ratings from the data for the training set of movies, excluding the hold-out set. At each time period, our personalized RS updates its parameters and generates new predictions for the hold-out movies. These predictions allow us to evaluate the RS algorithm’s performance in terms of regret and other relevant metrics. To contextualize the RS algorithm’s effectiveness, we compare its performance against the following benchmarks:

- **Aggregate Rating:** This algorithm predicts ratings based on aggregated ratings (average rating) for each user without leveraging specific movie features. This serves as a benchmark as the personalized RS also starts from aggregated ratings and updates as more information arrives. Given the absence of a learning mechanism in this benchmark, we expect its performance measures to remain constant over time.
- **User with Known Preferences:** This algorithm predicts ratings using the user’s known 51-dimensional preference vector, which consists of a linear preference over the top 50 most frequently mentioned tags and the aggregated rating. This preference vector is estimated by regressing the user’s actual ratings for all watched movies onto these 51 features. The user’s preference is assumed to be fully known from the outset and remains constant over time. This serves as the best performance achievable by a self-exploring user. Thus, any gap between this algorithm and the personalized RS reflects the gap factor g characterized in our theoretical analysis.
- **User with Learning:** This algorithm is similar to the previous one, with the key difference being that the user learns according to Algorithm 1. Like the RS algorithm, we maintain the actual sequence of ratings in the data and update the preference parameters for search features over time. It starts from the prior, assigning weight one to the average

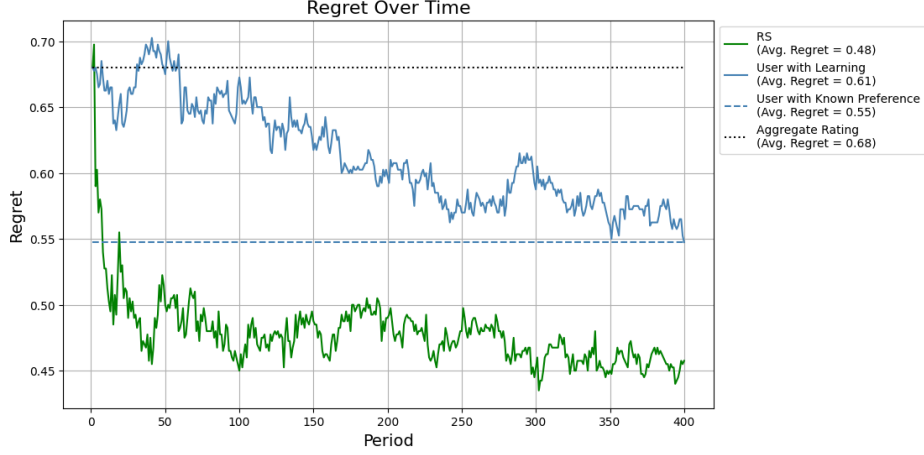


Figure 3: Comparing Learning Models- Regret (All Learning Models)

rating and zero weights to the remaining features, and updates as new ratings are observed. At any time period, the algorithm predicts ratings for all movies in the hold-out set based on their features, allowing us to evaluate its performance.

Figure 3 displays the performance of all four algorithms over 400 periods, aggregated across 100 simulations. Several key insights emerge from this figure. First, we observe that the RS outperforms all three benchmarks in the hold-out test set, demonstrating its ability to identify and leverage key patterns in user behavior. Second, there is a consistent gap between the regret under *RS* and the *User with Known Preferences*, which highlights the intrinsic information advantage of the RS and the gap between the first-best and the first-best based on search features. Third, we see that the RS quickly outperforms the user with known preferences, emphasizing its efficiency due to low-rank learning. This finding is particularly important as we do not impose any specific rank assumption that forces r to be lower than 51; rather, the personalized RS algorithm identifies the rank in a data-driven manner.

Next, we focus on additional performance accuracy measures that evaluate how well each algorithm predicts the ranking of items. Specifically, we use two commonly employed accuracy metrics: (1) *F1-Score*, which compares the top 10 recommendations from the model with the actual top 10 recommendations in the hold-out set [Chang et al., 2015], and (2) *Normalized Discounted Cumulative Gain (nDCG)*, an evaluation metric that assesses the quality of a ranked list by comparing the actual ranking with the ideal (perfect) ranking [Järvelin and Kekäläinen, 2002]. Both of these metrics are widely adopted in the literature on recommendation systems and collaborative filtering [Koren et al., 2021].

Figure 4 illustrates the performance of different algorithms in terms of F1-Score and nDCG.

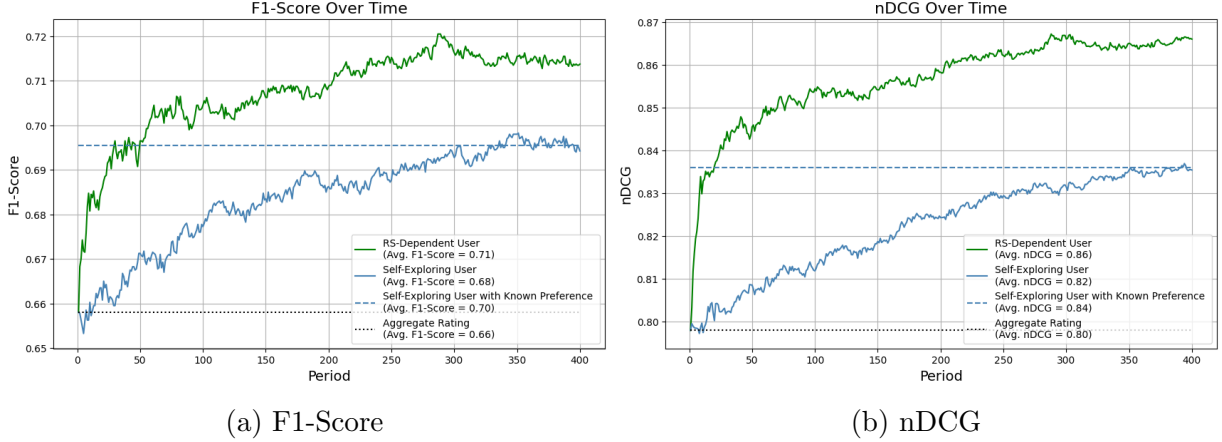


Figure 4: Performance of different algorithms using F1-Score and nDCG metrics

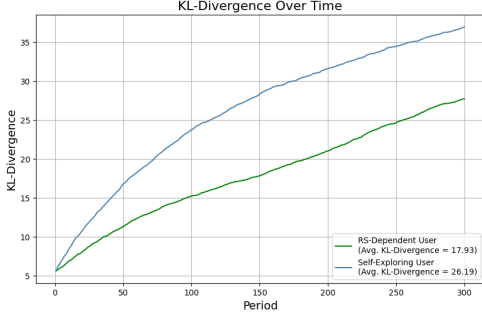
As shown in both figures, the personalized RS quickly outperforms all other benchmarks, highlighting its efficiency and inherent information advantage.

In summary, our findings highlight the information advantage of the personalized RS algorithm, offering a rational explanation for why users become dependent on algorithms. This is significant because prior literature has often cited factors such as time-inconsistent preferences and search costs to justify algorithmic dependence [Allcott et al., 2022, Korganbekova and Zuber, 2023]. However, as our analysis suggests, there is a clear limitation for users in the context of experience goods, which rationally forces them to rely on personalized RS, even with zero search cost and time-consistent preferences.

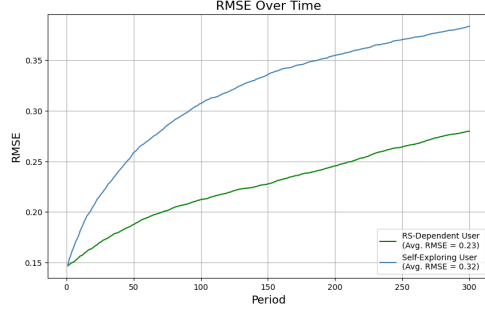
5.3 Implications for Users' Preference Learning

As shown in our theoretical and empirical analysis so far, RS-dependence brings substantial welfare gains for users, making it a rational strategy. However, this dependence also has implications for users' preference learning, as it alters the prior experience from which they resolve uncertainty about their preferences. In this section, we explore the implications of RS-dependence for users' learning and their ability to make independent decisions without the assistance of the RS.

We focus on the two user types studied in this paper: self-exploring users and RS-dependent users. Unlike in §5.2, where we maintain the user's consumption sequence, in this analysis, we modify the sequence according to Algorithms 2 and 3 to examine how each algorithm influences users' preference learning. However, we still remain within the set of movies that the user has actually rated in the data to avoid model-based evaluation. Specifically, for each user, we only allow consumption of the movies that they have already watched, excluding the



(a) KL Divergence



(b) RMSE

Figure 5: User learning under different algorithms

hold-out set of 20 movies.

We begin with a prior set of preferences that reflects the average taste, meaning the user’s prior weight for the aggregated rating feature is one, and their weight for all other features is zero. In each round, both self-exploring and RS-dependent users choose a movie from the available set, consume it, realize the utility, and update their preference parameters accordingly. We then measure the extent of learning by comparing the updated preferences with the prior preferences. If the system is learning effectively, we expect to see a larger difference between the updated preferences and the prior. To quantify this difference, we use two key measures: (1) Kullback-Leibler (KL) divergence, which is commonly used to assess the difference between two probability distributions, and (2) Root Mean Square Error (RMSE), which calculates the square root of the average squared differences between the mean preference parameters. These measures help evaluate how much the user has learned over time.

Figure 5 illustrates the learning outcomes for both self-exploring and RS-dependent users, measured using KL divergence and RMSE. As both figures demonstrate, the difference from the prior increases at a faster rate for the self-exploring user compared to the RS-dependent user. This suggests that the self-exploring user learns more efficiently over time. It is important to note that in this analysis, both user types begin with the same prior preferences, so the observed differences reflect the relative learning rates of the two approaches. The self-exploring user appears to benefit more from exploring a wide variety of movies, which contributes to faster learning, while the RS-dependent user, although benefiting from personalized recommendations, shows a slower rate of preference learning.

The finding in Figure 5 indeed highlights that following personalized recommendations comes at the expense of the user’s ability to learn. To quantify the impact of this trade-off by

a metric comparable to welfare, we turn to the measure of *counterfactual regret*, as outlined in Equation (11) and Definition 4. This measure allows us to assess how the RS algorithm influences the user’s independent decision-making ability by comparing their performance with different strategies. We consider three separate user types for this analysis:

- **Self-Exploring User:** This user chooses movies on their own and updates their preferences based on their realized utility.
- **RS-Dependent User:** This user relies on the personalized RS for their movie choices and updates their preferences upon consuming the algorithm’s recommendations.
- **RS-Dependent User Counterfactual:** This user follows the personalized RS recommendations in all prior periods, but in each period of the counterfactual evaluation, they make their own choices (without the algorithm’s help).

If RS-dependence truly acts as a barrier to preference learning, we should observe that the RS-Dependent User Counterfactual experiences higher regret compared to the Self-Exploring User and the RS-Dependent User. This would suggest that although RS-dependence provides short-term welfare gains by offering better recommendations, it limits the user’s ability to independently make decisions in the long term, thereby hindering their learning.

The results presented in Figure 6 underscore the trade-off between the benefits of following personalized recommendations and the cost in terms of independent decision-making ability. As shown in the figure, the two lines for the RS-Dependent User and Self-Exploring User resemble the results in Figure 3, but with the key difference that the sequence of consumed movies has changed due to the different algorithms being applied. The red line, representing counterfactual regret, illustrates the amount of regret an RS-Dependent User incurs when making decisions independently (i.e., without relying on the personalized recommendation system). This line shows a persistent gap between the expected regret (from following the RS) and the counterfactual regret (from independent decision-making).

Importantly, the expected counterfactual regret for the RS-Dependent User is consistently higher than the expected regret for the Self-Exploring User.⁹ This finding suggests that although following personalized recommendations reduces expected regret, it comes at the expense of users’ independent decision-making ability. This finding is important for several reasons. First, it highlights the trade-off between welfare gains and learning ability. Second, it raises concerns about dependency on personalized RS systems, particularly in contexts where independent decision-making is critical (e.g., to avoid adversarial AI attacks or to

⁹It is worth emphasizing that the counterfactual regret for the self-exploring user is the same as the expected regret.

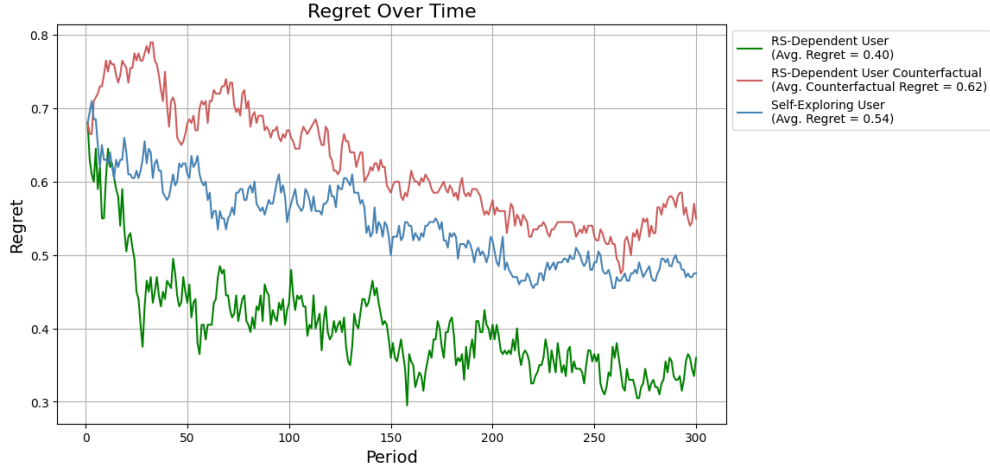


Figure 6: Comparison of regret and counterfactual regret for different algorithms

maintain a high level of user autonomy). Thus, our analysis of learning outcomes emphasizes the need to carefully balance the benefits of personalized algorithms with the potential risks of over-dependence.

5.4 Policy Implications

Our findings from §5.2 and §5.3 reveal a crucial trade-off between welfare and learning. This raises the question: is it possible to design a policy that effectively balances these two objectives?

We explore a specific class of policies that introduce randomness into the availability of the recommendation system. With this random availability, RS-dependent users are required to make their own decisions during certain periods. This is expected to boost users' preference learning while still maintaining some of the benefits provided by the personalized RS. Specifically, we define these policies using a single parameter p , which controls the probability that the recommendation system will be unavailable. When the personalized recommendation system is available, the RS-dependent user follows the algorithm; when it is unavailable, the user makes a decision independently based on her updated preferences. Notably, when the personalized recommendation system is always available (i.e., $p = 0$), the outcomes are consistent with those for the RS-dependent user. Conversely, when the recommendation system is unavailable (i.e., $p = 1$), the outcomes align with those of the self-exploring user. Please see Appendix C for the detailed description of the random availability algorithm.

As in §5.2 and §5.3, we measure both regret and counterfactual regret using the hold-out

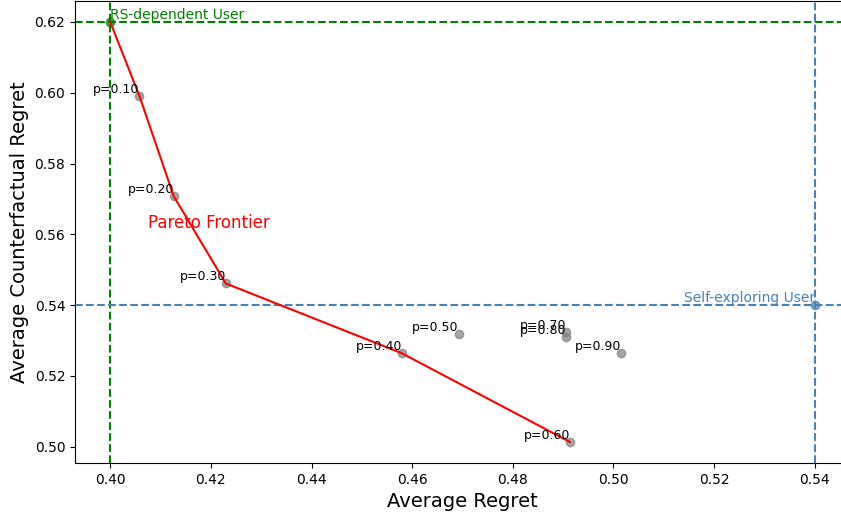


Figure 7: The performance of random availability policies in terms of regret and counterfactual regret

set of 20 movies for each user. For each random availability policy, we adjust the order of consumption according to the policy and assess its performance in terms of regret and counterfactual regret on the hold-out set. Figure 7 presents the results of this analysis. The figure clearly demonstrates the trade-off between regret and counterfactual regret, which is closely related to the classic exploration-exploitation dilemma. We show the Pareto Frontier for different random availability policies, where certain policies Pareto dominate the self-exploring strategy, achieving both lower expected and counterfactual regret. This finding suggests that random availability policies can provide superior alternatives to stringent data protection policies that entirely prohibit personalized recommendation systems.

Importantly, our results show that the Pareto Frontier approaches the optimal levels of expected regret achieved by the RS-dependent user. For instance, the policy with $p = 0.3$ achieves what can be considered the best of both worlds, by achieving counterfactual regret comparable to that of the self-exploring user while maintaining expected regret similar to that of the RS-dependent user. These findings indicate that even relatively simple policies, like random availability, can effectively balance the trade-off between welfare and learning. This offers valuable implications for platforms and users aiming to self-regulate their use of recommendation systems.

6 Discussion and Conclusion

Personalized recommendation systems have become a cornerstone of the digital ecosystem. However, growing user dependence on these algorithms has raised concerns among consumer protection advocates and regulators. In this work, we take an information-theoretic approach to examine the foundations of algorithmic dependence and its implications for users’ preference learning and independent decision-making—an increasingly critical issue given rising concerns about adversarial AI. We develop a utility framework in which users consume experience goods and sequentially learn their preferences, allowing us to analyze how personalized algorithms influence the learning process. Our theoretical results establish regret bounds for different user types based on their level of dependence on personalized recommendations. We show that algorithmic dependence is rational, as the welfare gains from following the personalized algorithm relative to self-exploration grow linearly over time. To complement our theoretical findings, we introduce an empirical framework that provides model-free measures of regret across different user types. We find that personalized algorithms generate significant welfare gains, but these gains come at the cost of users’ preference learning and independent decision-making. Finally, we demonstrate that simple policy interventions can help balance the trade-off between welfare and learning, offering valuable insights for both platforms and users.

In summary, our study makes several important contributions to the literature. From a substantive standpoint, we provide a comprehensive analysis of how personalized recommendation systems influence both welfare and learning outcomes, combining theoretical and empirical models. While these algorithms improve welfare by offering better product recommendations, they can also hinder users’ learning and independent decision-making ability. Unlike prior research, which has primarily focused on issues such as privacy, fairness, and polarization, our work shifts attention to algorithmic dependence and its implications for independent decision-making and autonomy. Therefore, our work contributes to the policy debate by uncovering the foundations of algorithmic dependence and emphasizing its negative effects on users’ ability to make independent decisions, offering insights that are particularly pertinent in light of the growing concerns surrounding adversarial AI.

Methodologically, we develop a theoretical framework to study algorithmic dependence and establish theoretical regret bounds based on users’ reliance on personalized algorithms. A key innovation of our approach is its ability to capture the information advantage of these algorithms through a low-rank assumption and access to experience features unavailable to users. Additionally, we introduce a counterfactual regret measure that serves as a

valuable benchmark for assessing the impact of adversarial AI. From a policy perspective, we demonstrate that straightforward exploration-based strategies can effectively balance the trade-off between welfare and learning. Our findings provide valuable insights for both managers and consumers. For managers, we propose that achieving a balance between performance and user learning is feasible at a low business cost. Similarly, our results offer self-regulation insights for consumers, enabling them to manage their own dependence on recommendation systems by taking simple steps.

Nevertheless, our paper has certain limitations that open avenues for future research. First, our findings are largely based on the established theories on user learning. One could design a long-run randomized experiment and verify these findings in the field. Second, our paper focuses on experiential preference learning. Future research can extend our work to different forms of learning (e.g., learning how to perform a task) and study the impact of algorithms on those learning outcomes. Finally, our paper studies exogenous levels of dependence on personalized algorithms to quantify the downstream consequence of this dependence. Future work can endogenize this aspect and examine the mechanisms behind this algorithmic dependence.

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Appendices

A Analytical Derivation of Bayes Updating Rule with Gaussian Noise

Proof. At any given time t , we have an updated belief about θ_i which is normally distributed as:

$$\theta_i \sim \mathcal{N}(\mu_{i,t}, \Sigma_{i,t}) \quad (17)$$

New data comes in the form of $A_{i,t}$ (a $d \times 1$ vector of action attributes at time t) and $U_{i,t}$ (the utility observed from taking action $A_{i,t}$). Given the new observation $(A_{i,t}, U_{i,t})$, the likelihood function (probability of observing $U_{i,t}$ given $A_{i,t}$ and θ_i) is normal with mean $A_{i,t}^T \theta_i$ and variance σ_ϵ^2 . The precision (inverse of the covariance matrix) of the prior distribution for θ_i is $\Sigma_{i,t}^{-1}$, and the precision of the new data is $\frac{1}{\sigma_\epsilon^2} A_{i,t} A_{i,t}^T$.

Therefore, the updated precision matrix (posterior precision) is the sum of the prior precision and the precision of the likelihood:

$$\Sigma_{i,t+1}^{-1} = \Sigma_{i,t}^{-1} + \frac{1}{\sigma_\epsilon^2} A_{i,t} A_{i,t}^T \quad (18)$$

The updated mean combines the prior mean and the new data, weighted by their respective precisions. The weight for the prior mean is its precision $\Sigma_{i,t}^{-1}$, and the weight for the new data $U_{i,t}$ is $\frac{1}{\sigma_\epsilon^2}$:

$$\mu_{i,t+1} = \Sigma_{i,t+1} \left(\Sigma_{i,t}^{-1} \mu_{i,t} + \frac{1}{\sigma_\epsilon^2} A_{i,t} U_{i,t} \right) \quad (19)$$

□

B Details of the Empirical Framework

Table A1 presents the set of top tags in the MovieLens data.

Table A1: Top 100 Movie Lens Data Tags

Top 1-34	Top 35-68	Top 69-100
original	pg-13	unlikely friendships
mentor	cinematography	passionate
great ending	redemption	very interesting
catastrophe	light	dramatic
dialogue	intense	relationships
good	family	so bad it's funny
great	corruption	independent film
chase	not funny	murder
runaway	unusual plot structure	sexy
good soundtrack	twists & turns	drinking
storytelling	entirely dialogue	childhood
vengeance	surprisingly clever	complex
story	pornography	creativity
weird	transformation	lone hero
drama	cult film	atmospheric
greed	adapted from:book	based on book
great acting	happy ending	first contact
imdb top 250	very funny	entertaining
culture clash	death	narrated
brutality	life & death	friendship
fun movie	social commentary	obsession
adaptation	stylized	based on a book
criterion	interesting	loneliness
life philosophy	enigmatic	sexualized violence
suspense	fight scenes	oscar (best supporting actress)
melancholic	harsh	very good
predictable	police investigation	gunfight
visually appealing	revenge	stereotypes
talky	justice	underrated
great movie	quirky	secrets
oscar (best directing)	excellent script	nudity (full frontal - brief)
clever	feel-good	
destiny	gangsters	
fantasy world	violence	

C Algorithm for the Random Availability Policies

In Section 5.4, we propose the policies with random availability. We show the detailed pseudo-code in Algorithm 4. Most parts of this algorithm are largely similar to Algorithm 3. The main difference is that the algorithmic recommendation is only available with a probability p .

Algorithm 4 Choice and Learning for the RS-Dependent User with Stochastic RS Availability

Input: $\mu_{i,0}^{(\theta)}, \Sigma_{i,0}^{(\theta)}, \mu_{i,0}^{(\gamma)}, \Sigma_{i,0}^{(\gamma)}, F, \mathcal{A}, \mathcal{T}, p$
Output: $\mathcal{H}_{i,\mathcal{T}}, \{\mu_{i,t}^{(\theta)}, \Sigma_{i,t}^{(\theta)}\}_{t=1}^{\mathcal{T}}, \{\mu_{i,t}^{(\gamma)}, \Sigma_{i,t}^{(\gamma)}\}_{t=1}^{\mathcal{T}}$

- 1: **for** $t = 0 \rightarrow \mathcal{T}$ **do**
- 2: $\xi_{i,t} \sim \text{Bernoulli}(p)$ ▷ Determine RS Availability
- 3: **if** $\xi_{i,t} = 1$ **then**
- 4: $\tilde{\gamma}_{i,t} \sim N(\mu_{i,t}^{(\gamma)}, \Sigma_{i,t}^{(\gamma)})$ ▷ RS: Distribution Sampling
- 5: $A_{i,t} \leftarrow \text{argmax}_{A_j \in \mathcal{A}} \sum_{k=1}^r \tilde{\gamma}_{i,k,t}^T F_k(A_j)$ ▷ RS: Recommendation Selection
- 6: **else**
- 7: $\tilde{\theta}_{i,t} \sim N(\mu_{i,t}^{(\theta)}, \Sigma_{i,t}^{(\theta)})$ ▷ User: Distribution Sampling
- 8: $A_{i,t} \leftarrow \text{argmax}_{A_j \in \mathcal{A}} \sum_{k=1}^s \tilde{\theta}_{i,k,t}^T A_{k,j}$ ▷ User: Action Selection
- 9: **end if**
- 10: Refer to Algorithm 3 for belief updating steps.
- 11: **end for**
