User Preferences in Recommendation Algorithms

The influence of user diversity, trust, and product category on privacy perceptions in recommender algorithms

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ABSTRACT

The use of recommendation systems is widespread in online commerce. Depending on the algorithm that is used in the recommender system different types of data are recorded from user interactions. Typically, better recommendations are achieved when more detailed data about the user and product is available. However, users are often unaware of what data is stored and how it is used in recommendation. In a survey study with 197 participants we introduced different recommendation techniques (collaborative filtering, content-based recommendation, trust-based and social recommendation) to the users and asked participants to rate what type of algorithm should be used for what type of product category (books, mobile phones, contraceptives). We found different patterns of preferences for different product categories. The more sensitive the product the higher the preference for content-based filtering approaches that could work without storing personal data. Trust-based and social approaches utilizing data from social media were generally rejected.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; • **Information systems** → *Web searching and information discovery*; Social recommendation; • **Software and its engineering** → E-commerce infrastructure;

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KEYWORDS

Recommender Systems, Privacy, User Perceptions, Trust, Acceptance

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1 INTRODUCTION

Recommender systems have become pervasive on the Internet and are used in almost every domain ranging from e-commerce, tourism, health, to even news recommendation. These systems typically rely on data from end users as well as meta-data on items to generate recommendations. Novel approaches utilize even more sensitive data (e.g. location data, social media data) to improve recommendation accuracy. However, data that is stored is potentially exploitable for different ends than initially intended. Scandals of data-misuse and security breaches are in the news regularly and users are confronted with the choice: "Do I trust this service provider with my data?" Independent of technological advances such as privacy-aware recommendation algorithms [17], user perceptions dominate the acceptance of technology [5]. User perceptions are inherently context-dependent [20] and may shift drastically with little changes such as the item category of a recommendation. In this study we investigate exactly this change and how it is dependent on user diversity factors such as computer self-efficacy, privacy concerns, and trust.

2 RELATED WORK

Several different recommendation techniques exist, such as collaborative filtering, content-based recommendation, trust-based and social recommendations [1, 14], as well as hybrid forms, which combine different techniques to overcome weaknesses of the singular ones. Among these, collaborative recommendation is most commonly used and most commonly combined with other techniques [4, 11]. An early example of a hybrid recommender system is Amazon's item-to-item collaborative filtering [13].

To further improve accuracy of recommendations, Zhou et al. [26] proposed a hybrid system of collaborative filtering and social networks. Using user-generated tags and the knowledge of relations between users, the quality of recommendations could be improved significantly. Similarly, O'Donovan et al. [21] proposed an approach to enhance collaborative filtering: Instead of matching similar user profiles, trust is measured as the percentage of correct predictions by profile. Using the general correctness of a profile and the correctness with respect to a particular item as two separate factors, these so called trust-based systems could decrease error rates up to 22%. However, not only accuracy matters [6, 16].

In general, users are not aware of how a search and filter algorithm work. In many cases, they are not aware that, e.g., the news they consume in social networks or news feeds is filtered at all [9]. Further, how a recommendation was generated by the recommender system at hand is often not transparent to the user. This might decrease trust in the system [10]. Explanations such as: "other customers bought..."/ "customers, who bought X, also bought..." have proven to increase acceptance of recommender systems.

Previous work has focused on evaluating recommendation using the quality of the generated recommendations. However, the user's preferences regarding technical details becomes increasingly important in times where the users' digital responsibility is discussed. Additionally, research on technology acceptance has shown that user factors such as age, gender, and self-efficacy in the use of technology impact the willingness to use a system [24]. Further, different perceptions of trust [15] and concerns [12, 19, 25] about privacy influence whether users are willing to provide personal data to an Internet service provider [23]. It is, however, unclear to what extent these factors influence acceptance of a recommendation algorithm given a certain product category.

Our Contribution. In our study we investigate the effect of different product categories on acceptance of different recommendation algorithms. We further investigate the effect of user diversity on this evaluation and try to determine what shapes the acceptance of different algorithm techniques in e-commerce.

3 METHOD

To investigate which recommendation technique and which type of algorithm users prefer in relation to different product categories, we conducted an online survey implemented on the platform SurveyMonkey. The survey was sent to 250 recipients in Germany in April 2018 and in April 2017 using convenience sampling[1]. The first sample was drawn from university students, while the second sample was drawn by snowball-sampling from the social networks of the authors. The survey consisted of three parts: First, we asked participants for demographic factors. We next measured computer self-efficacy, privacy concerns, institution-based trust and disposition to trust. The third part was used to assess the acceptance of different recommendation algorithms for three different product

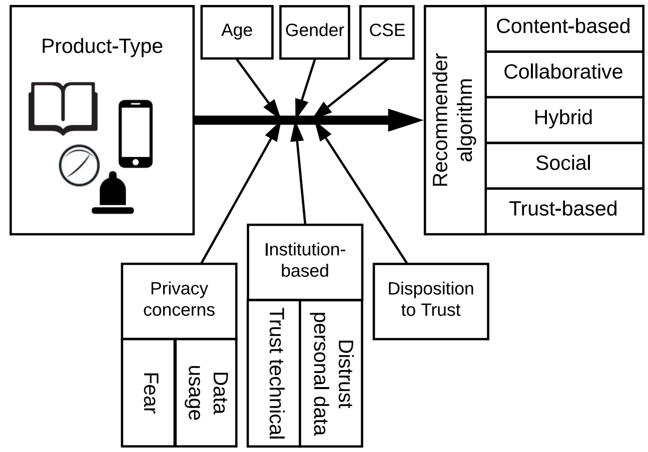

Figure 1: The research model of this study. We try to determine the influence of user-diversity factors on the recommendation algorithm preferences.

categories. Fig. 1 shows the research model of our investigation with the surveyed variables:

3.1 Demographic factors

The demographic factors we measured were age in years and gender (female or male). To understand the influence of *computer self-efficacy* (CSE) we used a construct with 8 items by Beier [3] which we extended by 2 additional items. The scale reliably measures the beliefs about control and self-efficacy in technology settings. In our sample it showed a good internal reliability (Cronbach's $\alpha = .84$) according to DeVellis [8].

3.2 Privacy concerns

Next, we asked our participants about their perceptions of privacy using Internet services. We used seven items adapted from Xu et al., Li et al. and Morton et al. [12, 19, 25]. These items were grouped into two scales. First, *privacy concerns fear*, which measures the generalized fear that personal data is "insecure" when stored online. Second, *privacy concerns data usage* measures the concerns that users have with the misusage of their personal data. The *privacy concerns fear* scale showed acceptable internal reliability using Cronbach's $\alpha = .785$, similar to the *privacy concerns data usage* scale that showed a Cronbach's $\alpha = .733$.

3.3 Institution-based trust

To separate the general fears about sharing personal data from the distrust in the infrastructure of the Internet, we measured institution-based trust using six items from McKnight et al. [15]. These items were grouped into two scales: The first scale called *personal data* measures to what degree a user distrusts that his personal data is used only as intended by service providers on the Internet. The second scale called *technical* is used to measure the trust that a user has in the technical infrastructure to ensure privacy on the Internet. The *institution-based distrust personal data*

[1] The samples did not differ qualitatively, see additional material for comparisons.

scale showed acceptable reliability of Cronbach's $\alpha = .74$, while the *technical* scale showed good reliability ($\alpha = .833$).

3.4 Disposition to Trust

We next presented participants six items that measure the disposition to trust in general (see also McKnight et al. [15]) independent of the context at hand. This scale showed an acceptable reliability ($\alpha = .725$).

3.5 Recommendation Algorithms and Products

The last section contained questions regarding the acceptance of different recommendation algorithms and their application in different product categories. We explained how five different techniques of recommendations work, what personal data they use and how they generate recommendations.

For *content-based* recommendation we explained that these algorithms try to analyze item-to-item similarity and recommend products that are similar to the items a user has shown interest in.

For *collaborative filtering* we explained that the algorithm stores user choices and tries to find other users with similar interests. It then recommends options that were well-received choices of similar users. For *hybrid* algorithms we explained that the algorithm would rely on both item-to-item similarity and user-to-user similarity to generate recommendations.

Trust-based recommendations, we explained, would require the user to explicitly pick users whose recommendations they liked to improve their own recommendations. Lastly, for *social* recommendations we explained that the users could grant access to social media data to utilize friendship relations to improve recommendations. All items were measured on a six-point-Likert scale (1 - disagree very much, 2 - disagree, 3 - rather disagree, 4 - rather agree, 5 - agree, 6 - agree very much).

The interaction scenario we presented had the participant imagine having to buy a new interesting book for themselves, a new mobile phone, and a contraceptive. The order of products was randomized between participants, order of recommendations systems not.

3.6 Hypotheses

We assume that approaches that require more data are less accepted than recommendation approaches that use less personal data (H_1). The sensitivity of the product should influence acceptance of recommendations accordingly (H_2). We further assume that general disposition to trust boosts acceptance of recommendation (H_3), while privacy concerns hinder acceptance (H_4). Older age (H_5), lower CSE (H_6), and being female (H_7) are expected to lower acceptance.

3.7 Statistical Procedures

We analyzed our results with descriptive statistics using means, standard deviations and 95% within-subject confidence intervals using Morey's method [2, 18]. For all scales we used principal component analysis to ensure the factor structure of the variables. We used the Kaiser-Meyer Olkin criterion to ensure sample adequacy and tested sphericity of our data using Bartlett's χ^2 test. We used Pearson correlations to measure associations between variables and report the correlation coefficient r, as well as an asymmetric 95% confidence interval that is generated by population bootstrapping [7]. To test our hypotheses we conducted an mixed-effect linear model [22] and report significant effects and correlations. Further details on the analyses can be found in the additional materials[1].

4 RESULTS

The data was analyzed using R Version 3.5 and RMarkdown[2]. We first describe our sample and then report our findings.

4.1 Description of the Sample

In total we had 197 participants that filled out our survey, 97 of which were female. The average age was $M = 31.2$ years ($SD = 12.1$). The sample showed a medium-high computer self-efficacy $M = 3.93$ ($SD = 0.81$), and relatively low privacy concerns (fear: $M = 2.90$, $SD = 0.96$; data usage: $M = 2.23$, $SD = 1.01$). Age is distributed relatively equal across genders ($t(193) = 0.636$, $p = .53$).

4.1.1 *Correlations of independent variables.*

To help understand our sample better, we can look at the Pearson correlations of our independent variables (see Table 1). It is interesting to note that privacy concerns seem to decrease with age, while the trust in the technical infrastructure of the Internet increases with age. In contrast, people with higher computer self-efficacy have more pronounced privacy concerns and show higher distrust towards online service providers to handle their data with care and at the same time show lower trust in the technical infrastructure. In general, trust and concerns seem to show a consistent picture. Interestingly, the disposition to trust only correlates with trust in the technical infrastructure.

4.2 Tests of our hypotheses

To understand how the individual products influence the acceptance of the five algorithms under study we plot the means of acceptance and their 95% confidence intervals by product (see Fig. 2). The non-overlapping confidence intervals indicate that there is indeed evidence for different preferences for algorithms depending on the product type, which is confirmed by our mixed-effect linear model. Acceptance for book recommendations are higher for collaborative filtering and content-based approaches. In contrast, hybrid approaches are accepted for books and mobile-phones alike. Approaches that utilize data from social networks such as trust-based or social recommendation algorithms are generally rejected in our sample.

Beyond the effects of product category and algorithm we found that gender influences acceptance as well in our analysis. This is true in general (men show a higher acceptance $M_{♂} = 3.1$, $M_{♀} = 2.78$, $p < .05$) and product-specific: here the difference between genders is strongest for contraceptives ($M_{♂} = 2.84$, $M_{♀} = 2.41$). Further, acceptance for recommendations decreases with age ($r = -.05$, $p < .01$), computer self-efficacy ($r = -.13$, $p < .001$), privacy concerns ($r = -.35$, $p < .001$), and increases with trust in the technical infrastructure ($r = .34$, $p < .001$). Disposition to trust has no influence on acceptance of recommendations.

[2]The full analysis of our data can be found in the additional files and retrieved as a markdown website at http://communication-science.com/openscience/recsys2018/.

Table 1: Correlation table of our independent variables

Variable	*M*	*SD*	1	2	3	4	5	6
1. Age	34.10	49.76						
2. Computer self-efficacy	3.93	0.81	-.04					
			[-.18, .10]					
3. Privacy concerns fear	2.90	0.96	-.16*	.33**				
			[-.29, -.02]	[.20, .45]				
4. Privacy concerns data usage	2.23	1.01	-.15*	.23**	.44**			
			[-.28, -.00]	[.09, .36]	[.32, .55]			
5. Institution-based distrust personal data	2.40	0.99	-.07	.21**	.59**	.27**		
			[-.21, .07]	[.07, .34]	[.49, .67]	[.13, .39]		
6. Institution-based trust technical	3.03	0.88	.16*	-.21**	-.24**	-.11	-.20**	
			[.01, .29]	[-.34, -.07]	[-.37, -.10]	[-.25, .04]	[-.34, -.06]	
7. Disposition to trust	3.08	0.64	.09	.01	.04	.12	.06	.22**
			[-.05, .23]	[-.13, .15]	[-.10, .18]	[-.02, .26]	[-.08, .20]	[.08, .35]

Note. *M* and *SD* represent mean and standard deviation. Values in square brackets indicate the 95% confidence interval. the confidence interval is a plausible range of population correlations that could have caused the sample correlation [7]. * indicates p < .05. ** indicates p < .01.

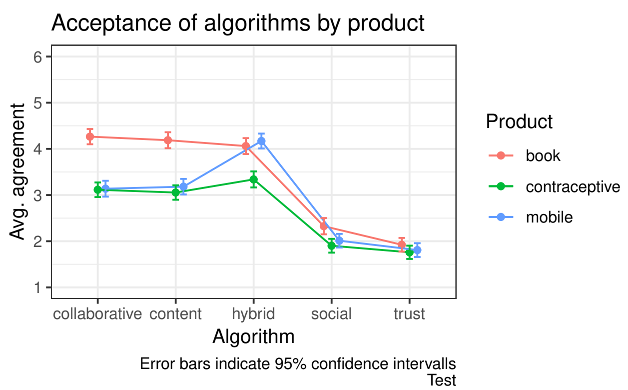

Figure 2: Means of the acceptance of individual algorithms by product category. The confidence intervals refer to within-subject comparisons using Morey's method.

5 DISCUSSION

In our study we investigated the effects of product types and user diversity factors on the acceptance of different recommendation algorithms. We found evidence for different acceptance patterns depending on product type and user factors. These findings are not unexpected, however they have to our knowledge not been quantified yet.

It is notable that approaches that utilize data from social media are generally rejected, although these seem to provide results increasingly well [26]. Further, no user-factors seem to influence the preference for any of the tested algorithms. The effects found in this study could be influenced by a cultural bias and only reflect on the German perspective of privacy and trust. Future work should elaborate on contrasting cultural effects on privacy and trust.

It may be arguable whether or not users can adequately assess what algorithm would satisfy their "real" requirements. It can be assumed that even though we explained the algorithms, users do not fully understand how the algorithms work behind the scenes—tensor decomposition and deep neural nets are not easily explained. A lot of the results depends on the description of the algorithms, which can be found in the additional materials. Further research should also work on finding descriptions that are adequate, comprehensible, and do not overemphasize either privacy or utility.

Further, satisfaction with the actual recommendation results could differ from their judgment in this study. Users merely rely on what type of data is stored and decide whether they consider this data to be worthy to be stored for recommendations for a given product category.

This is nevertheless informative. For example, when generating explanations for a specific product category only certain information could be used to inform the users. Only highly involved customers should be expected and asked to connect their social media profile with an e-commerce platform. Following these results, recommender systems should help users find relevant products using the least amount of data needed to create interesting and possibly serendipitous recommendations. They should be aware of what products are sensitive from a users perspective.

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