

THE EFFECTS OF TRANSPARENCY AND FEEDBACK ON CUSTOMER INTENTION FOR MOVIE RECOMMENDER SYSTEMS

Research-in-Progress

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Abstract

The problem of choosing the right product that will best fit the consumers' taste and preferences also extends even in electronic commerce. However, e-commerce could create a technological proxy for this social filtering process that is called Recommender Systems (RS). RS has the potential to support and improve the quality of the decisions consumers make when searching for and selecting products and services online, aiding users in decisions on matters related to personal taste. However, previous researches on RS have focused on the accuracy of the systems' algorithms, with little emphasis on interface issues and the user's perspective. This study identified transparency and feedback as some of the possible ways to evaluate recommender systems based from the users' perspective. The goals of this paper are to focus on examining and identifying the roles of transparency and feedback in recommender systems and how it affects the user's attitude towards the system.

Keywords: Recommender Systems, Transparency, Feedback

Introduction

One of the hardest decisions that people face in dealing with products and services that they want to purchase is how to choose the right product that will best fit their tastes and preferences. Because of this, people tend to seek recommendations and the most common way for people to decide is to ask their friends or relatives for suggestions. This problem also extends to the e-commerce field. However, in e-commerce a technological proxy for this social filtering process was created, known as online recommender systems (RSs). RSs constitute a web technology that proactively suggests items of interest to users, based on their objective behavior or explicitly stated preferences (Pu and Chen 2010). According to Medhi and Dakua (2005), RSs act as personalized decision guides, aiding users in decisions on matters related to personal taste. RSs have the potential to support and improve the quality of the decisions consumers make when searching for and selecting products and services online. Industry experts and researchers agree that the emergence of these systems is also important for reducing information overload and maximizing the benefit that can be gained from e-commerce. That is why RSs are often regarded as an important application in e-commerce.

Because of the importance and benefits brought about by RSs in the field of e-commerce, many researchers have addressed this topic. However, most previous research on RSs has focused on the statistical accuracy of the algorithms driving the systems, with little emphasis on interface issues and user perspectives (Pu and Chen 2010; Swearingen and Sinha 2002). Because studies tackling user perspectives are relatively scarce, in this research, we identified two factors that could affect the behavioral intentions of users.

This paper offers a fresh perspective on online recommender systems by looking at how the interaction between users and such systems influences a user's intention to reuse the technology. We identified transparency and feedback as two possible factors that could increase interaction between users and RSs that would result in effectively evaluating RSs from the user's perspective. Thus, this research focused on examining and identifying the roles of transparency and feedback in RSs and how they affected users' behavior toward the recommender system.

The main objectives of this research were to examine the roles of transparency and feedback on the behavioral intentions of users to reuse a recommender system. Specifically, the study aimed: 1) to explore how transparency affects user attitudes regarding RS reuse, 2) to ascertain how feedback affects user attitudes regarding RS reuse, and 3) to identify factors which affect the behavioral intention of users regarding RS reuse. Thus, we set an online experiment to see the effects of transparency and feedback on the recommendation process for user evaluations of RSs. The results would contribute to identify the roles of transparency and feedback on recommender systems

Literature Review and Research Model

Personalized Recommender System

According to Resnick and Varian (1997), recommender systems (RSs) were originally defined as systems in which "people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients." However, the definition of these systems has evolved over the years, giving a broader perspective and a more general definition now. RSs can now be defined as an automated and sophisticated decision support system that provides a personalized solution briefly, without going through a complex search process (Lee et al. 2007). RSs intend to provide people with recommendations for products they will appreciate, based on their past preferences, purchasing history, and demographic information (Ziegler et al. 2005). Because of the demonstrated benefits and advantages of RSs, they have gained popularity on the web, both in research systems and online commerce sites that offer recommendation systems as one way for consumers to find products they might like to purchase.

Typically, the effectiveness of recommender systems has been indexed by statistical accuracy metrics. However, satisfaction with a recommender system is only partially determined by the accuracy of the algorithm behind it (Swearingen and Sinha 2002). Xiao and Benbasat (2007) stated that the design of a RS or recommendation agent (RA) consists of three major components, which are: input, where user preferences are elicited, explicitly or implicitly; process, where recommendations are generated; and output, where recommendations are presented to the user. According to Pu and Chen (2010), numerous studies to make RSs more accurate and efficient have been undertaken previously; however, most of them have common critical limitations. So far, research on RS evaluation has focused primarily on algorithm accuracy for generating recommendations and, especially, in examining the objective prediction accuracy of such systems. Xiao and Benbasat (2007) supported this by saying that research on

RAs has focused mostly on process, which consists of developing and evaluating the different underlying algorithms that generate recommendations (Cosley et al. 2003; Swearingen and Sinha 2002), while failing to focus on, and adequately understand, input and output design strategies. They further stated that most of the review articles regarding RAs (Herlocker et al. 2004; Montaner et al. 2003; Sarwar et al. 2000; Schafer et al. 2001; Zhang 2002) provided either evaluations of different recommendation-generating algorithms, focusing primarily on criteria such as accuracy and coverage, or taxonomies of currently available RAs, mostly in terms of the underlying algorithms and techniques, without paying much attention to other design issues. However, from the customer's perspective, the effectiveness of RAs is determined by many factors aside from the algorithms (Swearingen and Sinha 2002), including the characteristics of RA input, process, output, source credibility, and product-related and user-related factors. That is why Pu and Chen (2010) noted that other researchers are now also investigating user experience issues, such as identifying determinants that influence user perceptions of RSs, effective preference elicitation methods, techniques that motivate users to rate items that they have experienced, methods that generate diverse and more satisfying recommendation lists, explanation interfaces, trust formation with recommenders, and design guidelines for enhancing a recommender's interface layout.

Communication Support

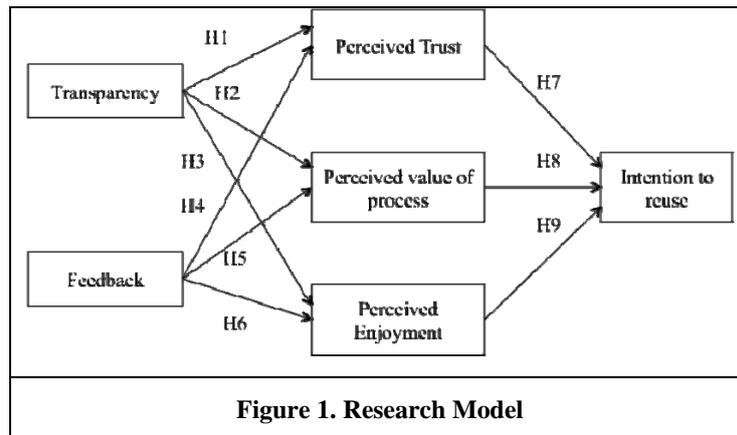
Communicate support ensures that shoppers can communicate their opinion with recommender agents to share or control their preference (Zhu et al. 2010). In other words, sometimes, users want to change their opinion or preferences when they get information that is not suitable to their interest. To resolve these problems, media should make sure their information suitable to users. Kim and Benbasat (2006) suggested that displaying trust-assuring arguments that include more controlling information to users are able to increase users' trusting belief. According to adaptation-level theory, user judgements are separate as different levels such as past experience, a context and treatment (Helson 1964). When recommender systems deliver recommended items, users only get recommendations. However, users' judgement for recommendation quality if recommender systems provide additional functions to change or treat the results by users. These vividness presentation make users increase trusting belief. That is because recommender systems make transparent control environment, and that may lead the representational richness of a recommending environment (Kim and Benbasat 2006).

More recently, researchers have begun to examine issues related to users' subjective opinions and to develop additional criteria to evaluate recommender systems. In particular, they suggest that user satisfaction does not always correlate with high recommender accuracy (Pu and Chen 2010; Wang and Benbasat 2009). However, none of these studies have focused on the roles of feedback or transparency. The works mentioned above lack a general definition and evaluation framework of what constitutes an effective and satisfying recommender system from the user's perspective. Previous papers also failed to discuss how the interaction between users and RSs influences users' reuse of the technology (Xiao and Benbasat 2007). Thus, in this study, we attempted to address these limitations by identifying two external factors that enhanced the interaction between users and RS--feedback and transparency--as ways to effectively evaluate recommender systems from the user's experience.

Research Framework

The technology acceptance model (TAM), of Davis (1989), was used as the ground theory to develop the model for this research. The key purpose of TAM is to provide a basis for tracing the impact of external variables on internal beliefs, attitudes, and intentions. Based on this, in the study, we tried to identify relationships between transparency, feedback, internal factors (perceived trust, perceived value of process, perceived enjoyment) and the behavioral intention of users to reuse a recommender system as Figure.1.

Previous research has shown that expert systems that act as decision guides need to provide explanations and justifications for their advice (Buchanan and Shortcliffe 1984). In the context of recommender systems, understanding the relationship between the input to the system (ratings made by user) and output (recommendations) allows the user to initiate a predictable and efficient interaction with the system (Gretzel and Fesenmaier 2006).



In this study, we identified transparency as one way to effectively evaluate recommender systems from the user's perspective. Specifically, transparency allows users to meaningfully revise the input to improve recommendations, rather than making "shots in the dark." By allowing users to review their initial ratings, they will be able to reassess their decision, based on their tastes and preferences.

Transparency aims to increase understanding and entails offering the user insight into how a system works, for example, by offering explanations for system behavior and the results from the system. Lee and See (2004) states that appropriate trust depends on how well the capabilities of a system are conveyed to the user. Transparency has also been found to influence user confidence in recommendations provided by the system. Thus, as the system becomes more transparent, users will perceive that the system is trustworthy.

H1: Transparency increases the user's perceived trust of the recommender system.

Bilgic and Mooney (2005) argued that a system's ability to make its reasoning transparent can contribute significantly to user acceptance of the system's suggestions. Because of this, if the user fully understands the whole procedure with regard to how the system was able to provide recommendations, then users will find the recommendation more reliable and trustworthy. Thus, process transparency is believed to increase the perceived value and overall acceptance of RSs. Transparency is thus expected to be an important factor in determining whether a recommendation will be accepted and evaluated positively.

H2: Transparency increases the user's perceived value of the process of the recommender system.

Many researchers have emphasized that transparency has an impact on other aspects of user perceptions (Pu and Chen 2010). User perception affects enjoyment: people find the system enjoyable if the whole system and procedure is easy and convenient to use. If the user understands how a system works and can predict system actions and outcomes, then the user can focus on his or her task, instead of trying to figure out the system. Thus, they will enjoy using the system.

H3: Transparency increases the user's perceived enjoyment of using the recommender system.

In this study, feedback is defined as the process by which the effect or output of an action is "returned" to modify the next action after users getting recommendations. The concept of feedback in this study includes the system's ability to allow users to revise their preferences, to customize received recommendations, and to request a new set of recommendations. It is assumed that by doing this, recommendation results will be more appropriate to the users. According to Pereira (2000), increased user control over the interaction with recommendation agents results in increased trust in the system. When users are given more control to revise their preferences at any given point in time, the user will consider the results more useful and effective. Thus, the user will be more confident in the results.

H4: Feedback increases the user's perceived trust of the recommender system.

The ability of the system to produce highly personalized recommendations based on the system's capability to identify user tastes and preferences is important in the personalization processes involved in producing a positive attitude towards the services the system provides (Gretzel and Fesenmaier 2006). If the user understands how the procedure can predict outcomes and how the whole process works, and the user has opportunities to reassess initial decisions, the user will find the whole procedure to be valuable and important. Thus, users will have a better understanding of the reasons behind the recommendations.

H5: Feedback increases the user’s perceived value of the process of the recommender system.

According to Cramer et al. (2008), giving users more control gives them more opportunities for a more entertaining and enjoyable personalized experience. Giving users more opportunity to interact with the system and providing them with more chances to modify their preferences helps them to understand the procedure better, which leads them to enjoy the whole process.

H6: Feedback increases the user’s perceived enjoyment in using a recommender system.

In this study, perceived trust is defined as the user’s willingness to believe in the information from a system or make use of its capabilities (Cramer et al. 2008). The concept of trust consists of trust in the intentions of a system (goal alignment) and trust in the competence of the system. Competence is seen as the perceived skill of the system, i.e., the extent to which it is able to offer the right recommendations. The perception of the alignment of goals of the system and the user’s goals, coupled with a belief that a system will perform its task competently, form the basis of trust (Cramer et al. 2008). Because of this, perceived trust will drive users to reuse a recommender system.

H7: Perceived trust positively affects the intention to reuse a recommender system.

The value of the process lies in its ability to identify a user’s tastes and preferences. Its potential to produce highly personalized recommendations is crucial because personalization processes result in more positive attitudes toward the services a system provides (Chau and Lai 2003). Customization attracts customer attention and fosters loyalty and personalized content increases the user’s motivation to elaborate on items suggested by a recommender system. Thus, the evaluations of the system’s capacity to capture their preferences and provide useful suggestions are expected to affect their intention to reuse the system (Gretzel and Fesenmaier 2006).

H8: Perceived value of the process positively affects intention to reuse a recommender system.

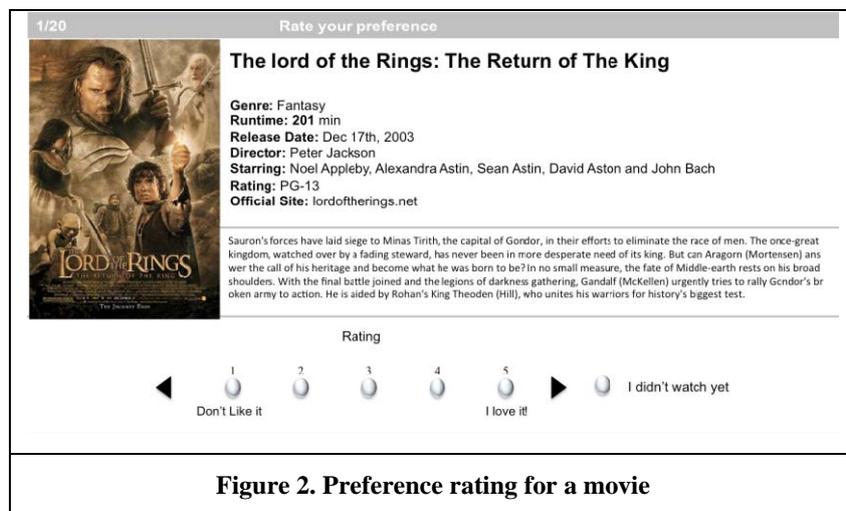
Perceived enjoyment can be defined as the extent to which the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use (Gretzel and Fesenmaier 2006). According to Gretzel and Fesenmaier, there is increasing evidence that enjoyment of one’s interaction with technology has important consequences for one’s perception and subsequent evaluation of the technology and can be manipulated by the design of the technology. On the other hand, great effort, lack of transparency, and having to answer irrelevant questions will presumably decrease a user’s enjoyment.

H9: Perceived enjoyment positively affects the intention to reuse a recommender system.

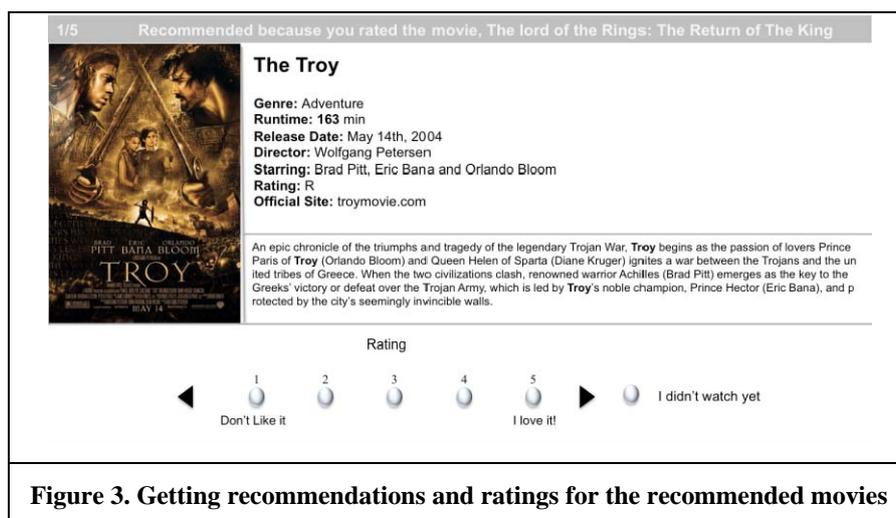
Table 1. Experimental Treatments in the Study		
Group	Recommendation procedures	Description
A	1) Rating on 20 movies 2) Getting 5 movie recommendations 3) Rating on the 5 recommended movies	Basic
B	1) Rating on 20 movies 2) Reviewing ratings 3) Getting 5 movie recommendations 4) Rating on the 5 recommended movies	Transparency
C	1) Rating on 20 movies 2) Getting 5 movie recommendations 3) Rating on the 5 recommended movies 4) Getting 5 new movie recommendations 5) Rating on the new recommendations	Feedback
D	1) Rating on 20 movies 2) Reviewing ratings 3) Getting 5 movie recommendations 4) Rating on the 5 recommended movies 5) Getting 5 new movie recommendations 6) Rating on the new recommendations	Transparency + Feedback

Methodology

A movie recommender system was selected as the context of the study. Specifically, participants will be asked to rate different movies that will be presented by the movie recommender system and evaluate the recommendations it will provide. A total of 120 participants will be invited to participate in the experiment. The experiment will involve the manipulation of two factors (Transparency and Feedback) with two levels per factor, thus leading to a 2x2 full-factorial between subjects design as shown in Table 1. The group A (low transparency, low feedback) will be manipulated by asking the participants to rate the movies that will be presented to them just like the regular movie recommendation system. The group B (high transparency, low feedback) will be manipulated by presenting same procedures with the group A and by asking the subjects to review the ratings they initially made on the movies presented to them. The group C (low transparency, high feedback) will be manipulated by asking the subjects to rate again the recommendations that will be given to them by the system based from the ratings they initially gave in. And the group D (high transparency, high feedback) will be presented same procedures with the t group A and giving a chance to review their ratings on movies and feedback on recommendations they get.



In the experiment, we will vary the procedures for getting preference data and presenting recommendations (Table 1). The respondents will randomly be assigned into one of the four groups. All groups use the same recommendation algorithm, item-to-item collaborative filtering (Sarwar et al. 2001).



Group A has the basic recommendation procedure. After subjects rate their preferences for the 20 movies shown in Figure 2 to get their preference data, they will get five movie recommendations. Then, the subjects will rate the recommended movies (Fig. 3). We will collect information of Group B have the same procedure as Group A and then an additional step to review and update their ratings after rating the 20 movies.

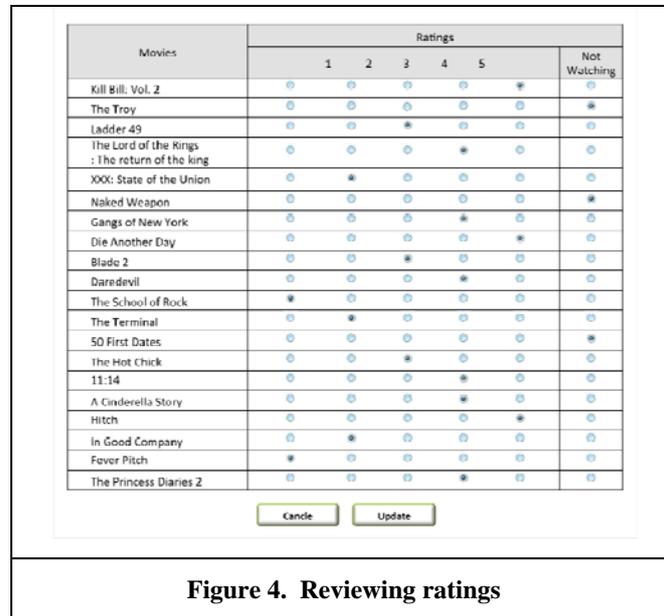


Figure 4. Reviewing ratings

Upon receiving the recommendations in each of the four groups, participants will be prompted by the system to proceed to the evaluation survey. All groups will be asked to answer the questionnaire, but they go through different experimental procedures (Group A-D). The survey will ask them to respond to the questions about their evaluation of the recommendations and their perceptions of their interaction with the four different recommendation procedures. The questionnaire will be developed from materials discussed and tested previously and consist of 24 items. Because the items in the questionnaire are derived from existing literature, they will be modified slightly to fit the context of the study. Each item will be measured on a seven-point Likert scale, ranging from “strongly disagree”(1) to “strongly agree”(7). The sources of the scale items from each of the constructs are summarized in Table 2.

Upon receiving the recommendations, participants will be prompted by the system to proceed to the evaluation survey. The survey will ask them to respond to questions about their evaluation of the recommendation and their perceptions of their interaction with the system.

Dimensions	# of Items	Sources
Transparency	4	Pu and Chen (2010)
Feedback	3	Pu and Chen (2010)
Perceived Trust	3	Flavian, Guinaliu, and Gurrea (2005); Gefen and Straub (2003)
Perceived Value of Process	4	Gretzel and Fesenmaier (2007)
Perceived Enjoyment	3	Gretzel and Fesenmaier (2007)
Behavioral Intention to Use	3	Pu and Chen (2010)

Expected Results

User evaluation for RS is important in recent IS field because many customer need to find out more interesting items to them. In this study, we will investigate the role of transparency and feedback on the behavioral intention of the

users to use/reuse a recommender system. To identify the effects of transparency and feedback on web recommender systems, this study can contribute to describe the importance for transparency and feedback on movie recommender systems with experimental design and find out the importance of transparency and feedback for recommending process to deliver recommendations to users.

According to reviewing recommended results through users themselves, this research also will identify other factors that induced users to use/reuse a recommender system. The results of the study are expected to show that both transparency and feedback positively and may affect perceived trust, perceived value of the process, and perceived enjoyment. The results can demonstrate that both factors can be considered as external variables that influence user attitudes and intentions in technology adoption. Furthermore, we can show the relationships among perceived trust, perceived value of the process, and perceived enjoyment positively and effects for user intentions to reuse a recommender system.

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