www.calsec.or.kr
http://dx.doi.org/10.7838/jsebs.2013.18.2.279

온라인 추천시스템에서 고객 사용의도를 위한 시스템 투명성과 피드백의 영향

Influences of Transparency and Feedback on Customer Intention to Reuse Online Recommender Systems

Januel L. Hebrado*, 이홍주(Hong Joo Lee)**, 최재원(Jaewon Choi)***

초 록

고객 취향에 가장 적합한 제품을 선택하는 것은 전자상거래에서 중요한 문제이다. 전자상거래 그러나 온라인 추천시스템으로서 알려진 소셜 필터링은 전자상거래에서 기술적 접근이 활발히 연구되어왔다. 온라인 추천시스템은 사용자의 개인적 취향과 관련하여 적절한 제품을 필터링하여 제공함으로서 사용자의 의사결정 품질을 향상시키는 것에 목적을 두고 있으며 그 결과 사용자의 제품 탐색과 선택에 대한 지원이 가능하다. 그러나 대다수 추천시스템의 선행연구들은 추천 알고리즘의 정확성을 향상시키는 것에 집중해 왔으며 사용자 기반의 인터페이스나 사용자 관점의 사용방식에 대한 연구는 매우 적은 실정이다. 추천시스템의 추천 상황에 대한 시스템 투명성과 사용자의 추천에 대한 피드백을 통한 추천방식 개선을 통하여 본 연구는 사용자 관점의 추천시스템 활용에 대한 시스템 투명성과 피드백의 영향력을 파악하고자 하였다. 실험을 통한 연구 결과에 따라, 시스템 투명성과 사용자 피드백 모두 추천시스템에 대한 사용자의 인지된 신뢰, 프로세스 가치, 인지된 즐거움에 영향을 주는 것으로 나타났다. 특히, 인지된 신뢰, 프로세스 가치, 즐거움은 사용자가 추천시스템을 지속적으로 사용하기 위한 의도를 향상시키는 것으로 나타났다.

ABSTRACT

The problem of choosing the right product that will best fit a consumer's taste and preferences extends to the field of electronic commerce. However, e-commerce has been able to create a technological proxy for the social filtering process, known as online recommender systems (RSs). RSs aid users in filtering products and decisions on matters relating 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. However, most previous research on RSs has focused on the accuracy of the algorithms, with little emphasis on user interface and perspectives. This study identified transparency and feedback as possible ways to effectively evaluate RSs from the user's perspective. Thus, this research focused

---

이 논문은 2010년도 정부재원(교육과학기술부 인문사회연구역량강화사업비)으로 한국연구재단의 지원을 받아 연구되었음(NRF-2010-332-B00182).
* Fulltime Lecturer, College of Business Administration, Adamson University
** Corresponding Author, Associate Professor, Department of Business Administration, Catholic University of Korea(E-mail : hongjoo@catholic.ac.kr)
*** Research Professor, Graduate School of Information, Yonsei University
2013년 03월 22일 접수, 2013년 05월 21일 심사완료 후 2013년 05월 24일 게재확정.

on examining and identifying the roles of transparency and feedback in recommender systems and how they affect users' attitudes toward the system. Results of the study showed that both transparency and feedback positively and significantly affected perceived trust, perceived value of the process, and perceived enjoyment. Furthermore, we found that perceived trust, perceived value of the process, and perceived enjoyment positively and directly affected users' intentions to use/reuse a recommender system.

키워드 : 추천시스템, 투명성, 피드백, 전자상거래, 재사용의도
Recommender System, Transparency, Feedback, E-Commerce, Reuse Intention

1. 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 [7, 38]. According to Medhi and Dakua [34], RSs aid users in filtering products and decisions on matters related to personal taste [42]. 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 accuracy of the algorithms, with little emphasis on user interface and user perspectives although some experimental studies have studied the role of transparency [38, 42, 43]. 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 performed an online experiment to see the effects of transparency and feedback on the recommendation process for user evaluations of RSs. We made four different recommendation processes by inserting steps to review ratings and give feedback on recommendations. We summarize related literature in Section 2 and address hypotheses and the research model in Section 3. Experiment procedures and data collection are stated in Section 4 and the results of the experiment are discussed in Section 5. We conclude with discussions and conclusions in Section 6.

2. Literature Review

2.1 Personalized Recommender System

According to Resnick and Varian [39], 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 [28]. RSs intend to provide people with recommendations for products they will appreciate, based on their past preferences, purchasing history, and demographic information [3, 18, 20, 50]. 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 [32, 35, 44, 45]. Xiao and Benbasat [47] 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 [38], 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 [47] 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 [12, 32, 44], while failing to focus on, and adequately understand, input and output design strategies. They further stated that most of the review articles regarding RAs [27, 10, 35, 40, 49] 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 [28, 30, 43], including the characteristics of RA input, process, output, source credibility, and product-related and user-related factors. That is why Pu and Chen [38] 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. Furthermore, from the early systems to date, most of the published empirical evaluations have focused on measuring only how close a recommender system predictions are to a user's true preferences [26].

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 [38, 46]. 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 [47]. 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.

2.2 Communication Support

Communication support ensures that shoppers can communicate their opinion with recommender agents to share or control their preference. In order 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. According to media richness theory [14, 15], less-rich communicative media should understand the limitations of that medium in the dimensions of feedback, multiple cues, message tailoring, and emotions. This means the more equivocal a message, the more cues and data needed to understand it, and media richness theory places communication mediums on a continuous scale that represents the richness of a medium and its ability to adequately communicate a complex message [16]. When recommender systems make recommendations to users with more communicative cues, the users can be more satisfied with the results of recommender systems which provide richer interactions.

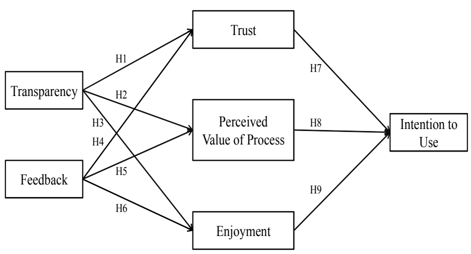
Xiao and Benbasat [47] suggested that displaying trust-assuring arguments that include more controlling information to users are able to increase users' trusting belief. According to adaptation-level theory, user judgements are separate as different levels such as past experience, a context and treatment. 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 [47].

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 [38, 46]. 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 [48]. 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.

3. Research Model

The technology acceptance model (TAM) [17] was used 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>. The researcch model was presented in our previous paper [25] without an empirical result [26] and this paper includes our empirical analysis based on the research model.

Previous research has shown that expert systems that act as decision guides need to provide explanations and justifications for their advice [5]. 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 [24].



〈Figure 1〉 Research Model

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 [31] 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 [4] 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 [38]. 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 [37], 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 [24]. 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. [13], 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 [13]. 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 [13, 22]. 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 [6]. 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 [24].

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 [24]. According to Gretzel and Fesenmaier [24], 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.

4. Methodology

A movie recommender system was selected as the context of the study. Specifically, respondents were asked to rate different movies that were presented by the movie recommender system and evaluate the recommendations it provided through a survey questionnaire. We used the preferences for movies from Netflix data to provide personalized movie recommendations. We selected 100 movies that were released in Korea from the Netflix data. There were 20 movies each from the genres of action, drama, comedy, science fiction, and animation. Movie information was obtained from a Korean movie portal, Naver Movies.

Subjects rated their movie preferences and evaluated the recommended movies. In the first stage, we showed 20 movies to obtain user preferences. Four movies were selected from each movie genre. According to Lee et al. [29], we needed to collect user preferences for more than 20 items to make reliable recommendations. Then, we recommended five movies among the remaining 80 movies on the basis of the user preferences obtained during the first stage and movie preferences from the Netflix data.

In total, 135 undergraduate students located in Seoul, Korea, were invited to participate in the study. The participants were pursuing a variety of majors at a university. In the experiment, we varied the procedures for getting preference data and presenting recommendations as shown in <Table 1>. The 135 respondents were randomly assigned into one of the four groups. All groups used the same recommendation algorithm, called item-to-item collaborative filtering [41].

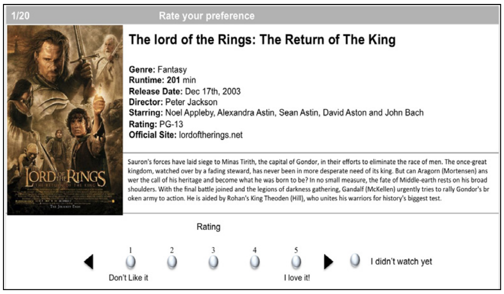
Group A had the basic recommendation

〈Table 1〉 Experimental Treatments in the Study

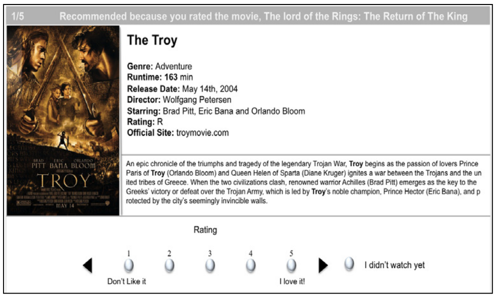
Group	Recommendation procedures	Description
A	1) Rating on 20 movies 2) Getting 5 movie recommendations 3) Rating on the 5 recommended movies	Basic
B	1) Rating on 20 movies 2) Reviewing ratings 3) Getting 5 movie recommendations 4) Rating on the 5 recommended movies	Transparency
C	1) Rating on 20 movies 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

procedure. After subjects rated their preferences for the 20 movies shown in <Figure 2>, they got five movie recommendations. Then, the subjects rated the recommended movies <Figure 3>. Group B had the same procedure as Group A and then an additional step to review and update their ratings after rating the 20 movies <Figure 4>. Group C had the same procedure as Group A. However, after the subjects rated the first recommended movies, they got new recommendations for five movies, based on the feedback for the first recommendation. Group D had the same procedure as Group A, with the added steps of reviewing their initial ratings, as in Group B, and reassessing the recommendations, as in Group C.

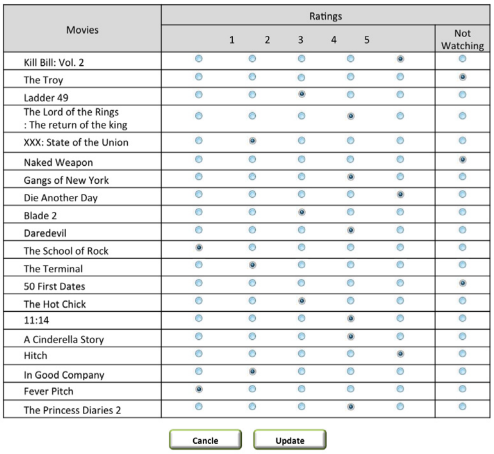
Upon receiving the recommendations in each of the four groups, participants were prompted by the system to proceed to the evaluation survey. All groups answered the questionnaire, but they went through different experimental procedures. The survey asked them to respond to the questions about their evaluation of the recommendations and their perceptions of their interaction with the four different recommendation procedures. The questionnaire was developed from materials discussed and tested previously and consisted of 24 items. Because the items in the questionnaire were derived from existing literature, they were modified slightly to fit the context of the study. Each item was 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>.



〈Figure 2〉 Preference Rating for a Movie



〈Figure 3〉 Getting Recommendations and Ratings for the Recommended Movies



〈Figure 4〉 Reviewing Ratings

〈Table 2〉 Sources of Questionnaire Items

Dimensions	Number of Items	Sources
Transparency	4	Pu and Chen [37]
Feedback	3	Pu and Chen [37]
Perceived Trust	3	Flavian et al. [21], Gefen et al. [23]
Perceived Value of Process	4	Gretzel and Fesenmaier [24]
Perceived Enjoyment	3	Gretzel and Fesenmaier [24]
Behavioral Intention to Use	3	Pu and Chen [37]

5. Results

The demographics of the 135 participants with valid responses are shown in <Table 3>. The gender of the respondents was almost evenly mixed, with 47% males and 53% females. As expected, most of the respondents in the four groups were in the same age bracket (20~29 years old) because they were all university students. Only about 1.5% of the respondents were below 20 years old and 2.2% of them were in the age range of 30~39 years old. Results also showed that more than 50% of the respondents used the Internet for 1~2 h per day while 33.3% of them used it for 3~5 h per day. Only 6.7% and 8.2% of the respondents, respectively, reported that they used the internet for less than 1 h and more than 5 h per day. Furthermore, results revealed that more than half (51.9%) of the respondents watched only one movie per month, while 35.6%, 8.9%, and 3.7% of them

〈Table 3〉 Demographics of the Respondents

	Group	A	B	C	D	Total
		Freq. (%)	Freq. (%)	Freq. (%)	Freq. (%)	Freq. (%)
Gender	Male	17(45.9)	15(42.9)	16(50.0)	16(51.6)	64(47.4)
	Female	20(54.1)	20(57.1)	16(50.0)	15(48.4)	71(52.6)
Age	11~19	0(0.0)	0(0.0)	1(3.1)	1(3.2)	2(1.5)
	20~29	36(97.3)	35(100.0)	29(90.6)	30(96.8)	130(96.3)
	30~39	1(2.7)	0(0.0)	2(6.3)	0(0.0)	3(2.2)
	> = 40	0(0.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)
Internet Usage	< 1 h/day	2(5.4)	3(8.6)	2(6.3)	2(6.5)	9(6.7)
	1~2 h/day	18(48.6)	19(54.3)	16(50.0)	17(54.8)	70(51.9)
	3~5 h/day	13(35.1)	11(31.4)	12(37.5)	9(29.0)	45(33.3)
	> 5 h/day	4(10.8)	2(5.7)	2(6.3)	3(9.7)	11(8.1)
Number of Movies/month	1 movie	15(40.5)	17(48.6)	19(59.4)	19(61.3)	70(51.9)
	2~3 movies	13(35.1)	14(40.0)	11(34.4)	10(32.3)	48(35.6)
	4~5 movies	7(18.9)	1(2.9)	2(6.3)	2(6.5)	12(8.9)
	> 6 movies	2(5.4)	3(8.6)	0(0.0)	0(0.0)	5(3.7)
Recommender System Experience	Yes	11(29.7)	5(14.3)	3(9.4)	5(16.1)	24(17.8)
	No	26(70.3)	30(85.7)	29(90.6)	26(83.9)	111(82.2)

watched two or three movies, four or five movies, and more than six movies per month, respectively. Regarding recommender system experience, 82.2% of the respondents reported having no experience in using such a system.

The collected data sets were analyzed using exploratory factor analysis (EFA) to check the validity of each dimension, such as transparency, feedback, perceived trust, perceived value of process, perceived enjoyment, and intention to reuse a recommender system as <Table 4>. The values of Cronbach's α were

〈Table 4〉 The Results of Exploratory Factor Analysis

Proposed Dimension		Extracted Dimensions	
Dimensions	Items	Factor Loading	Cronbach's α
Transparency (Trans)	The recommender system helps me understand why the items were recommended to me.	0.782	0.885
	The recommender system gives me a chance to review my preferences.	0.798	
	The recommender system gives me more control in telling what I want.	0.724	
	I understand why the movies were recommended to me.	0.781	
Feedback (FB)	The process provides an easy way to inform the system if I dislike/like the recommended item to get more refined ones.	0.797	0.802
	The recommender system gives me a chance to update the outcome of the recommended items based from my preferences.	0.738	
	The recommender system provides an easy way for me to get a new set of recommendations.	0.801	
Perceived Trust (Trust)	I think I can have confidence in the promises that the recommender system makes.	0.770	0.899
	I think that the recommender system has the necessary abilities to carry out its work.	0.791	
	I think that the recommender system knows its users well enough to offer them products and services adapted to their needs.	0.870	
Perceived Value of Process (PVP)	The task I had to complete provided a valuable means for capturing my preferences.	0.629	0.886
	I think I had a lot of influence over the recommendation process.	0.719	
	This recommender system is worth using when trying to find a movie that suits to my tastes and preferences.	0.584	
	The process the system made me go through was worthwhile.	0.550	
Perceived Enjoyment (PE)	I had fun completing the whole process of getting a recommendation using this system.	0.808	0.895
	Receiving a movie recommendation this way was enjoyable.	0.803	
	I expect that using mobile recommender system would be interesting.	0.743	
Behavioral Intention (IU)	I will use this recommender again.	0.669	0.953
	I will use this type of recommender frequently.	0.764	
	I prefer to use this type of recommender in the future.	0.755	

〈Table 5〉 Results of Convergent Factor Analysis (CFA)

Construct	The number of Items	AVE	Construct Reliability	Cronbach's α	Square root of AVE
Trans	4	0.745	0.921	0.885	0.863
FB	3	0.716	0.883	0.802	0.846
Trust	3	0.832	0.937	0.899	0.912
PVP	4	0.745	0.921	0.886	0.863
PE	3	0.827	0.935	0.895	0.909
IU	3	0.916	0.970	0.953	0.957

all greater than 0.7, indicating that each construct had high consistency. This result was also demonstrated by the values of the factor loadings. Additionally, one question item in the survey failing to meet the standard was deleted to boost the overall validity of the questionnaire survey.

To identify convergent and discriminant validity, we conducted confirmatory factor analysis (CFA). Usually, convergent validity indicates the extent to which measures for a variable act as if they are measuring underlying theoretical constructs because they share variance [41]. To test convergent validity among constructs and their items, we used averaged variance extracted (AVE), as suggested previously [19]. With these criteria, each construct must exceed the variance due to measurement error for that construct. As shown in <Table 5>, the AVE values for each construct were greater than 0.5, suggesting that the scales of the research model had convergent validity. Additionally, the reliability of the scales was evaluated using the values of construct reliability, which demonstrated sufficient reliability, because all values were greater than 0.80 (range, 0.8830.970).

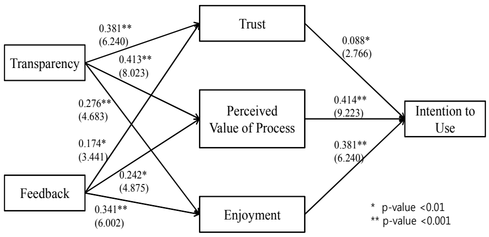
Discriminant validity indicates "the degree to which measures of two or more constructs are empirically distinct." [1]. Discriminant validity can be assessed by identifying that the AVE for each construct should be greater than the squared correlation between constructs. Thus, we conducted testing of discriminant validity using the square root of AVE, and it was found that the square roots of AVE of each construct were greater than the coefficients of each construct. According to Chin [8] and Compeau et al. [11], the square root of AVE should be greater than the variance shared among constructs and other constructs, which was the case in this study <Table 6>. In <Table 6>, elements shown on the diagonal in the matrix are the square root of the AVE. Thus, the constructs of the research model had discriminant validity.

Structural equation modeling (SEM) [9] was conducted using SmartPLS. <Figure 5> illustrates the explanatory power (R^2) of each latent independent variable for the entire model, with perceived trust (0.249), perceived value of the process (0.341), perceived enjoy-

〈Table 6〉 Discriminant Validity Results

Constructs	FB	IU	PE	PVP	Trans	Trust
FB	0.846					
IU	0.448	0.957				
PE	0.496	0.745	0.909			
PVP	0.474	0.756	0.624	0.863		
Trans	0.562	0.469	0.468	0.548	0.863	
Trust	0.388	0.575	0.433	0.707	0.478	0.912

ment (0.299), and intention to reuse (0.698). Based on the results, the proposed model is acceptable. Both transparency and feedback significantly and positively influenced perceived trust, perceived value of the process, and perceived enjoyment. The path coefficients of 0.381 ($p < 0.01$), 0.413 ($p < 0.01$), and 0.276 ($p < 0.01$), respectively, indicated that transparency directly impacts perceived trust, perceived value of the process, and perceived enjoyment, supporting H1, H2, and H3. Furthermore, path coefficients of 0.174 ($p < 0.01$), 0.242 ($p < 0.01$), and 0.341 ($p < 0.01$), respectively, indicate that feedback significantly influenced perceived trust, perceived value of the process, and perceived enjoyment, confirming the propositions of H4,

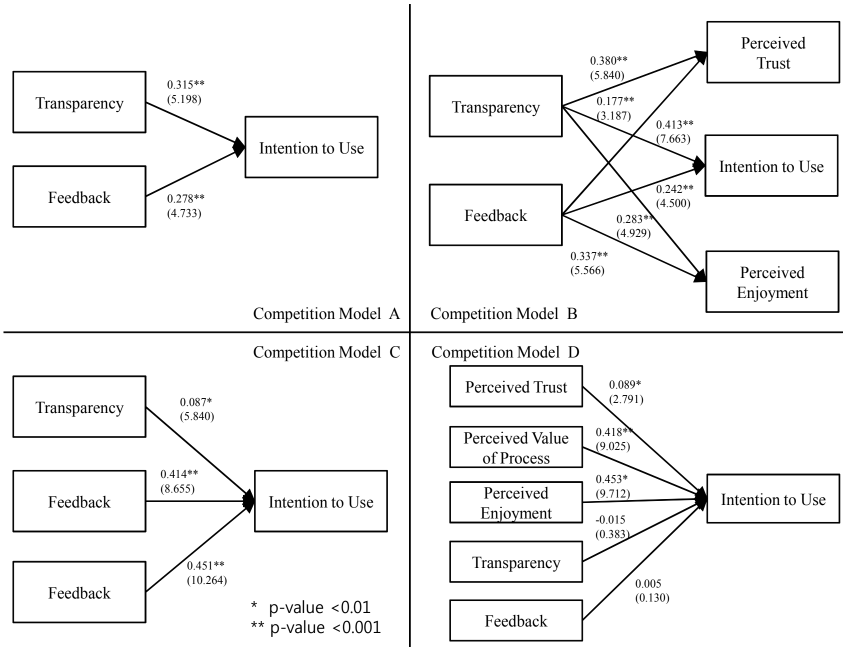


〈Figure 5〉 Analysis Results

H5, and H6.

Similarly, the results revealed that perceived trust, perceived value of the process, and perceived enjoyment significantly and directly influenced the intention of the user to reuse the recommender system, with path coefficients of 0.088 ($p < 0.05$), 0.414 ($p < 0.01$), and 0.449 ($p < 0.01$) respectively. This also means that perceived trust, perceived value of the process, and perceived enjoyment positively affected the intention of the users to reuse the recommender system. Thus, hypotheses 7, 8, and 9 were confirmed and supported.

To examine the mediating effects of trust, perceived value of the process, and enjoyment between intention to reuse and transparency/feedback, we used competition models, which were adopted from the method developed by Baron and Kenny [2]. The mediator test refers to a four-step method that attempts to examine mediating effects and proposes the following: (1) the independent variables (Transparency, Feedback) and the dependent variable (Intention to reuse) have significant relationships, (2) the independent variables (Transparency, Feedback)



〈Figure 6〉 Competition Models

and the mediators (Trust, Perceived value of the process, Enjoyment) have significant relationships, (3) the mediators (Trust, Perceived value of process, Enjoyment) and the dependent variable (Intention to reuse) have significant relationships, and (4) the combined independent variables and mediator reduce the direct effects of independent variables to dependent variables. Accordingly, when the direct effects of independent on dependent variables are significant, the mediating effects are partially mediated. On the other hand, if no significant relationship exists between independent and dependent variables, their effects are fully mediated. <Figure 6> suggests that the test results of competition models A, B, and C satisfy conditions 1, 2, and 3. Furthermore, competition model D also satisfied condition 4 in that, by incorporating mediators of the independent variables, the direct effects of independent on dependent variables (Transparency → Intention to reuse, Feedback → Intention to reuse) become insignificant. This result demonstrates that perceived trust, perceived value of the process, and perceived enjoyment fully mediate between the independent variables (Transparency, Feedback) and the dependent variable (Intention to reuse).

6. Discussion and Conclusions

In this study, we investigated the role of transparency and feedback on the behavioral intention of the users to use/reuse a recommender system. This research also identified other factors that induced users to use/reuse a recommender system. The results of the study showed that both transparency and feedback positively and significantly affected perceived trust, perceived value of the process, and perceived enjoyment. The results demonstrated that both factors can be considered as external variables that influence user attitudes and intentions in technology adoption.

Furthermore, we showed that perceived trust, perceived value of the process, and perceived enjoyment positively and directly affected user intentions to reuse a recommender system. Transparency most affected the perceived value of the process, strengthening the proposition that the more the system procedure is transparent to the user, the more the user will perceive the whole process and results to be valuable. The results also showed that feedback most influenced perceived enjoyment, validating the proposition that the more control the user is given, the more the user will enjoy the experience of using the system.

This study has both academic and practical implications. First, we propose a new conceptualization of transparency and feedback in recommender systems. In contrast to previous research, in this study, we used the combination of transparency and feedback to measure the effectiveness of recommender systems from the user's perspective. The paper deviates from the usual approach of seeking more refined algorithms and suggests, instead, that greater interaction, through transparency and feedback, and a recommendation agent, has added value for users. Second, the current work constitutes a pioneering effort to study empirically the effects of the combination of transparency and feedback on user behavior. The research model offers new mechanisms through which transparency and feedback influence users' behavioral intentions to adopt a technology, such as a recommender system. Finally, these results can guide system developers and online merchants as to how recommender systems can be improved by developing a system that is more transparent and a technology that allows the user to have more control. This will help to enhance the effectiveness of recommender systems in the field of ecommerce.

This study has some limitations. First, the study failed to consider that some users might be heavily tied to another recommender system and that it might be difficult for them to move or change to another recommender system, considering their past investment in another service. For example, users may be unwilling to use a new recommendation system because they have been actively using another service where they have already stored personal information or where they have made many past ratings. Second, almost all respondents were limited to one age group and location, making it difficult to generalize the results. Future research should examine a more diverse range of respondents to get a more generalizable result. Finally, the recommender system used in the study only offered one specific product (movies). Future studies should use other products or a range of products that are appropriate to, and will catch the attention of, the respondents.

References

[1] Bagozzi, R., Yi, Y., and Phillips, L., "Assessing Construct Validity in Organizational Research," Administrative Science Quarterly, Vol. 36, No. 3, pp. 421-458, 1991.

[2] Baron, R. and Kenny, D., "The Moderator-Mediator Variable Distinction in Social Psychological Research : Conceptual, Strategic, and Statistical Consideration," Journal of Personality and Social Psychology, Vol. 51, No. 6, pp. 1173-1182, 1986.

[3] Belkin, N. J. and Croft, W., "Information Filtering and Information Retrieval : Two Sides of Same Coin," Communications of the ACM, Vol. 35, No. 12, pp. 29-38, 1992.

[4] Bilgic, M. and Mooney, R., "Explaining Recommendations : Satisfaction Vs. Promotion," In M. van Setten, S. McNee, and J. Konstan (eds.), Beyond Personalization 2005-A Workshop on the Next Stage of Recommender Systems Research in Conjunction with the 2005 International Conference on Intelligent User Interface (IUI'05). New York, ACM Press, 2005.

[5] Buchanan, B. and Shortcliffe, E., "Rule-Based Expert Systems : The Mycin Experiments of the Stanford Heuristic Programming Project," Addison Wesley Publishing Company, Reading, MA, 1984.

[6] Chau, P. and Lai, V., "An Empirical Investigation of The Determinants of User Acceptance of Internet Banking," Journal of Organizational Computing, Vol. 13, No. 2, pp. 123-145, 2003.

[7] Chen, L. and Pu, P., "Interaction Design Guidelines on Critiquing-based Recommender Systems," User Modeling and User-Adapted Interaction Journal (UMUAI), Springer Netherlands, Vol. 19, No. 3, pp. 167-206, 2009.

[8] Chin, W., "Issues and Opinion on Structural Equation Modeling," MIS Quarterly, Vol. 22, No. 1, pp. 7-16, 1998.

[9] Chin, W., "The Partial Lease Square Approach for Structural Equation Modeling in Modern Methods for Business Research," M. G. A., ed., (ed.), Lawrence Erlbaum, Mahwah, NJ, pp. 295-336, 1998.

[10] Choi, J. and Lee, H. J., "An Integrated Perspective of User Evaluating Personalized Recommender Systems : Performance-driven or User-centric," The Journal of Society for e-Business Studies, Vol. 17, No. 3, pp. 379-394, 2012.

[11] Compeau, D., Higgins, C., and Huff, S., "Social Cognitive Theory and Individual

Reactions to Computing Technology : A Longitudinal Study," MIS Quarterly, Vol. 23, No. 2, pp. 145-158, 1999.

[12] Cramer, H., Evers, V., and Ramlal, S., "The Effects of Transparency on Trust in and Acceptance of a Content-based Art Recommender," User Modeling and User-Adapted Interaction Journal, Vol. 17, No. 6, pp. 734-749, 2008.

[13] Cosley, D., Lam, S., Albert, I., Konstan, J., and Riedl, J., "Is Seeing Believing? How Recommender Systems Influence Users' Opinions," In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Fort Lauderdale, FL, 585-592, 2003.

[14] Daft, R. L. and Lengel, R. H., "Information Richness: A New Approach to Managerial Behavior and Organizational Design," In : Cummings, L. L. and Staw, B. M. (eds.), Research in organizational behavior 6, JAI Press, Homewood, IL, pp. 191-233, 1984.

[15] Daft, R. L. and Lengel, R. H., "Organizational Information Requirements, Media Richness and Structural Design," Management Science, Vol. 32, No. 5, pp. 554-571, 1986.

[16] Daft, R. L., Lengel, R. H., and Trevino, L. K., "Message Equivocality, Media Selection, and Manager Performance: Implications for Information systems," MIS Quarterly, Vol. 11, No. 3, pp. 355-366, 1987.

[17] Davis, R., "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Technology," MIS Quarterly, Vol. 13, No. 3, pp. 319-340, 1989.

[18] Fayyad, U., Piatetsky-Shapiro, G., Smyth, P., and Uthurusamy, R., "Advances in Knowledge Discovery and Data Mining," AAAIpress/MIT press, 1996.

[19] Fornell, C. and Larcker, D., "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," Journal of Marketing Research, Vol. 18, No. 3, pp. 39-50, 1981.

[20] Frawley, W., Piatetsky-Shapiro, G., and Matheus, C., "Knowledge Discovery in Databases : An Overview," AI Magazine, Vol. 13, No. 3, pp. 57-70, 1992.

[21] Flavian, C., Guinaliu, M., and Gurrea, R., "The Role Played by Perceived Usability, Satisfaction, and Consumer Trust on Website Loyalty," Information and Management, Vol. 43, No. 1, pp. 1-16, 2006.

[22] Gefen, D., "E-Commerce : The Role of Familiarity and Trust," Omega, Vol. 28, No. 6, pp. 725-737, 2000.

[23] Gefen, D., Karahanna, E., and Straub, D., "Trust and TAM in Online Shopping : An Integrated Model," MIS Quarterly, Vol. 27, No. 1, pp. 51-90, 2003.

[24] Gretzel, U. and Fesenmaier, D., "Persuasion in Recommender System," International Journal of Electronic Commerce, Vol. 11, No. 2, pp. 81-100, 2006.

[25] Hebrado, J., Lee, H. J., and Choi, J., "The Role of Transparency and Feedback on

the Behavioral Intention to Reuse a Recommender System," In Proceeding of CONF-IRM 2011, Paper 8, 2011.

[26] Herlocker, J., Konstan, J., and Riedl, J., "Explaining Collaborative Filtering Recommendations," In Proceeding at the ACM 2000 Conference on Computer Supported Cooperative Work, pp. 241-250, 2000.

[27] Herlocker, J., Konstan, J., Terveen, L., and Riedl, J., "Evaluating Collaborative Filtering Recommender Systems," ACM Transactions on Information Systems, Vol. 22, No. 1, pp. 5-53, 2004.

[28] Jones, N. and Pu, P., "User Technology Adoption Issues in Recommender Systems," In Proceedings of Networking and Electronic Commerce Research Conference (NAEC2007), pp. 379-394, 2007.

[29] Lee, H., Kim, J., and Park, S., "Understanding Collaborative Filtering Parameters for Personalized Recommendations in e-Commerce," Electronic Commerce Research, Vol. 7, No. 3-4, pp. 293-314, 2007.

[30] Lee, H., Ahn, H., and Han, I., "VCR : Virtual Community Recommender Using the Technology Acceptance Model and the User's Needs Type," Expert Systems with Applications, Vol. 33, No. 4, pp. 984-995, 2007.

[31] Lee, J. and See, K., "Trust in Automation: Designing for Appropriate Reliance," Human Factors : The Journal of the Human Factors and Ergonomics Society, Vol. 42, No. 1, pp. 50-80, 2004.

[32] McNee, S., Albert, I., Cosley, D., Gopalkrishnan, P., Lam, S., Rashid, A., Konstan, J., and Riedl, J., "On the Recommending of Citations for Research Papers," In Proceeding Of ACM CSCW 2002, ACM Press, pp. 116-125, 2002.

[33] McNee, S., Lam, S., Konstan, J., and Riedl, J., "Interfaces for Eliciting New User Preferences in Recommender Systems," In Proceedings of the 9th International Conference on User Modeling, pp. 178-187, 2003.

[34] Medhi, D. and Dakua, J., "MovieReco: A Recommendation System," In Proceeding of World Academy of Science, Engineering and Technology, Vol. 4, pp. 70-75, 2005.

[35] Montaner, M., Lopez, B., and Dela Rosa, J., "A Taxonomy of Recommender Agents on the Internet," Artificial Intelligence Review, Vol. 19, No. 4, pp. 285-330, 2003.

[36] Ozok, A., Fan, Q., and Norcio, A., "Design Guidelines for Effective Recommender System Interfaces Based on a Usability Criteria Conceptual Model : Results from a College Student Population," Behaviour and Information Technology, Vol. 29, No. 1, pp. 57-83, 2010.

[37] Pereira, R., "Optimizing Human-Computer Interaction for the Electronic Commerce Environment," Journal of Electronic Commerce Research, Vol. 1, No. 1, pp. 23-44, 2000.

[38] Pu, P. and Chen, L., "A User-Centric Evaluation Framework of Recommender Systems," In proceedings of the ACM RecSys 2010 Workshop on User-Centric Evaluation of Recommender Systems and their Interfaces (UCERSTI), 2010.

[39] Resnick, P. and Varian, H., "Recommender Systems," Communications of the ACM, Vol. 40, No. 3, pp. 56-58, 1997.

[40] Sarwar, B., Karypis, G., Konstan, J., and Riedl, J., "Application of Dimensionality Reduction in Recommender Systems - A Case Study," In Proceeding of ACM WebKDD Workshop, 2000.

[41] Sarwar, B., Karypis, G., Konstan, J., and Riedl, J., "Item-based collaborative filtering recommendation algorithms," In Proceeding of WWW10, pp. 285-295, 2001.

[42] Schwab, D., "Construct Validity in Organizational Behavior," In L. L. Cummings and B. Staw (eds.), Research in Organizational Behavior, 12, JAI Press, Greenwich, CT, pp. 3-43, 1980.

[43] Sinha, R. and Swearingen, K., "The Role of Transparency in Recommender Systems," In Proceeding of CHI'02, pp. 830-831, 2002.

[44] Swearingen, K. and Sinha, R., "Interaction Design for Recommender Systems," In Proceeding of Interactive Systems (DIS2002), 2002.

[45] Tintarev, N. and Masthoff, J., "Survey of Explanations in Recommender Systems," In Proceeding for ICDE Workshops, pp. 801-810, 2007.

[46] Wang, W. and Benbasat, I., "Interactive Decision Aids for Consumer Decision Making in e-Commerce : The Influence of Perceived Strategy Restrictiveness," MIS Quarterly, Vol. 33, No. 2, pp. 293-320, 2009.

[47] Xiao, B. and Benbasat, I., "E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact," MIS Quarterly, Vol. 31, No. 1, pp. 137-209, 2007.

[48] Xiao, B. and Benbasat, I., "Product-Related Deception in E-Commerce : A Theoretical Perspective," MIS Quarterly, Vol. 35, No. 1, pp. 169-195, 2011.

[49] Zhang, Y., "Literature Review for Online Communities and Recommender Systems: State of the Art Paper," Unpublished doctoral dissertation, University of Minnesota, Minneapolis, 2002.

[50] Ziegler, C., McNee, S., Konstan, J., and Lausen, G., "Improving Recommendation Lists through Topic Diversification," In Proceeding of International World Wide Web Conference Committee (IW3C2), 2005.

저 자 소 개

Januel L. Herbrado	(E-mail : januel_lh@yahoo.com)
2005년	Bachelor of Science in Business Administration Major in Economics De La Salle University-Dasmariñas
2011년	Master of Business Administration, The Catholic University of Korea
2012년~현재	Fulltime Lecture, College of Business Administration, Adamson University, Philippines
관심분야	e-Business, Recommender Systems, Personalization

이홍주	(E-mail : hongjoo@catholic.ac.kr)
1997년	KAIST 산업경영학과 졸업
1999년	KAIST 테크노경영대학원 경영공학 (MS)
2006년	KAIST 테크노경영대학원 경영공학 (Ph.D)
2006년	MIT Center for Collective Intelligence, Post-doctoral Fellow
2007년~현재	가톨릭대학교 경영학과 부교수
관심분야	개인화, 집단지성, 모바일 비즈니스

최재원	(E-mail : jaewonchoi@yonsei.ac.kr)
2004년	가톨릭대학교 경영학과 졸업
2006년	가톨릭대학교 일반대학원 경영학과 (MS)
2006년	가톨릭대학교 일반대학원 경영학과 (Ph.D)
2010년~2011년	KAIST 테크노경영연구소 연수연구원
2011년~현재	연세대학교 정보대학원 연구교수
관심분야	웹 개인화, 집단지성, 모바일추천시스템, 클라우드컴퓨팅