EXAMINING THE EFFECTS OF PERSONALIZED APP RECOMMENDER SYSTEMS ON PURCHASE INTENTION: A SELF AND SOCIAL-INTERACTION PERSPECTIVE

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ABSTRACT

Personalized recommendations are generated by considering the preferences of a target user and similar users. Although explanations of recommendations affect the evaluations of personalized recommender systems (PRS), PRS evaluations have focused primarily on the perceived accuracy and novelty of the recommending algorithms. The goal of this study is to examine the effectiveness of using social interaction factors (self-referencing and social presence) to explain PRS. We developed six PRS for applications (apps) on smartphones by varying the level of social presence and self-referencing. We conducted Web-based experiments using these six types of PRS, and we then obtained participant evaluations of their social interactions and PRS. Our research model is designed to determine how social interactions, such as social presence and self-referencing, affect perceived accuracy and novelty, and in turn, how these affect satisfaction and intent to purchase. The results obtained demonstrate that the social context significantly increases the perceived accuracy and novelty of PRS. The results explain that perceived accuracy and novelty positively influence user satisfaction, and how satisfaction and perceived novelty affect purchase intention. In addition, we verify the effect of mediation on perceived accuracy, perceived novelty, and satisfaction. Thus, by integrating PRS performance and social interaction, this research contributes to improving our understanding of the social cognitive process related to user evaluation of PRS.

Keywords: Personalized Recommender Systems; Social Presence; Self-referencing; Apps; Perceived Accuracy; Perceived Novelty

1. Introduction

The emergence of user-based Web services and personalization technologies has allowed many companies to provide personalized content or services to users [Hill and Troshani 2010] and business intelligence [Foshay and Kuziemsky 2014; McBride 2014]. User-based Web services and personalization technologies refer to Web services and technologies that employ personal user information. Rapid improvements in Web, mobile facilities, and services have significantly increased the variety of choices available to customers, and have led to the development of a very large number of mobile software programs called “apps” (application programs for PCs and mobile devices, such as smartphones and tablets). Apps allow users to perform specific tasks on their desktops and mobile devices (e.g., iPads and Macintosh computers). For example, Apple OS X operates all programs as apps, and many Macintosh (Mac) users search for apps in Web-based app stores.

Several apps have been developed. For example, Apple’s App Store stocked more than one million apps in January 2015 [Gartner, 2013]. Most app store sales are made in recreational categories, such as entertainment, social

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networking, and music. Faced with the large amount of content available in many forms in an ultra-competitive environment, along with intense pricing pressure, would-be customers find it difficult to identify and select appropriate apps from among the many similar ones that are available [Herlocker et al. 2004]. Gartner [2013] reported that annual downloads from mobile app stores reached 102 billion in 2013, up from 64 billion in 2012, whereas total revenue reached $26 billion in 2013, up from $18 billion in 2012 (see Appendix 1). Therefore, app stores have had to devise methods for assisting customers in their search for appropriate apps that satisfy their needs.

Previous literature on recommender systems has considered online content, such as news and movies. However, app markets have changed recently with the availability of more than one million apps, and it is difficult for customers to easily find suitable apps on their mobile devices. App recommender systems are therefore important because in the app market context, they can reduce customer search cost while yielding better search results. To help customers find suitable apps, personalized recommender systems (PRS) have been developed, thus allowing the delivery of enhanced, customized information or products in response to Web searches [Liang et al. 2007; Tam and Ho 2005; Wang and Benbasat 2007]. PRS determine and employ user preferences in order to generate recommendations that help such users select personally helpful and interesting items [Benlian et al. 2012; Liang et al. 2007; Tam and Ho 2005; Herlocker et al. 2004]. Their purpose is to retain customers by making it less appealing or attractive for them to switch, and to facilitate customer searches for products or information [Shani and Gunawardana 2011; Hess et al. 2009; Xiao and Benbasat 2007]. PRS are based on the premise that users already exposed to relevant Web content seek less information and spend less time making decisions [Choi et al. 2014; Choi et al. 2011; Tam and Ho 2005, 2006].

To this end, previous studies on recommender systems have proposed various predictive metrics, such as accuracy, novelty, and variety, which differ from users' perceptual evaluations of app recommender systems [Shani and Gunawardana 2011; Palanivel and Sivakumar 2010; Adomavicius and Tuzhilin 2005; Herlocker et al. 2004]. Among those metrics, accuracy is important in order to ensure that recommended items are those items that users want to find based on their preference. Nevertheless, app stores cannot rely on the accuracy measure alone to evaluate recommender systems [Palanivel and Sivakumar 2010]. User behavior in terms of choice or purchase does not always correlate to high recommender accuracy [McNee et al. 2002]. For example, most users might already own a specific app if that app is very famous among users. In this case, the accuracy of a recommender system might not be effective. Therefore, improving only the accuracy of PRS in order to filter recommendations for those apps with which users are already familiar is not sufficient.

PRS novelty is another important aspect to consider when limiting irrelevant recommendations and providing new and worthwhile items to PRS users [Vargas 2011]. With novelty, PRS can deliver apps that are new to users. For this reason, this study focuses on accuracy and novelty because these are the most frequently used measures in assessing PRS [Shani and Gunawardana 2011].

However, the degree to which users value PRS remains unclear, as does how they arrive at values, because users generally receive an explanation of how PRS arrive at their recommendations. Explanations are important components of intelligent systems because they make system performance transparent to users [Wang and Benbasat 2007]. PRS explanations describe how the recommendations were generated and provided to users. Therefore, an explanation can transfer knowledge to users and help them make better decisions [Gregor and Benbasat 1999]. Choi et al. [2011] also found that PRS explanations improve user perception of how well systems perform. However, there is still a lack of understanding with regard to the value of PRS to users, and how users perceive value. In particular, understanding how customers arrive at their evaluations of PRS based on social interaction has been studied much less than evaluations based on forecasting metrics, such as accuracy and novelty [Choi et al. 2011; Hess et al. 2009; Wells et al. 2011].

The response to this gap by some studies has been to propose the use of PRS for functional interfaces and interactions between users as a method for helping these users make their decisions [Benlian et al. 2012; Komiak and Benbasat 2006; Kumar and Benbasat 2006; Liang et al. 2007; Wang and Benbasat 2007]. PRS can provide social interfaces (i.e., interfaces based on social interactions with others or self) to customers while considering user-based features [Xiao and Benbasat, 2007]. In contrast to research that investigates the relationship between system performance and user evaluation [Choi et al. 2011] the effect of social interaction on PRS, explanation of recommendations, and a list of users with similar preferences have not been evaluated. Therefore, in this study, we aim to examine the role of self and social interactions in the social cognitive process by identifying how they affect user evaluation of PRS from the user perspective. When users employ PRS to search for apps, they are usually confronted with several apps in the app store. Our study is unconcerned with the design of app recommender systems. Instead, we are interested in examining the impacts of the key characteristics of app recommender systems. The research questions of this study are as follows: First, how does user evaluation of app recommendations affect their decision-making in terms of perceived accuracy and novelty when purchasing apps? Second, how do the self and social interaction characteristics of the recommendation system affect user evaluation of the recommended outcomes (i.e., app recommendations)?

To this end, we designed app recommender systems that have varying degrees of self and social interactions, and we used them to conduct our experiments. This study has an important value in verifying that technology does not determine human action; rather, human action shapes technology [Bijker et al. 1987]. That is, human action that is performed during the selection and purchase of mobile apps determines the use of app PRS and their designs in order to improve the performance of app recommendation systems. This study also adds to the electronic commerce literature by examining the importance of effective self and social interaction interfaces in PRS during user evaluation. In addition, in this study, we propose measurement methods for user-perceived accuracy and novelty in app recommender systems. Although previous studies have focused on improving PRS measures, such as precision and recall [Shani and Gunawardana 2011; Herlocker et al. 2004], we measured perceived PRS performance (perceived accuracy and novelty) based on user-dependent PRS evaluation. The findings of this study can be used in the design of future PRS and the management of app stores.

2. Conceptual Background

2.1. Social Cognitive Process in PRS Use

The social cognitive process refers to information processing with regard to all persons, including the self, and the norms and procedures of the social world [Bandura 1986; Khang et al. 2012]. One component of the social cognitive process includes the perception of other people. Many app store users might employ information from any number of sensory channels when processing social cues in order to understand others because they are overwhelmed by the sheer volume of apps through which they must sort. To improve the search process, such users might turn to Web technologies to direct them to appropriate products. For example, users might review the opinion of other users, or employ search engines and PRS. These cues can be categorized or labeled in order to extract psychological meaning. In this study, we define the social cognitive process as the behavioral intention of users formed through outcome expectancy.

The other component of the social cognitive process is the self, which is a social object that needs to be understood [Khang et al. 2012]. The self can serve as a cognitive filter through which other people are perceived. Even when users know which apps match their interests and needs, they might still fail to make sound decisions. This is because customers tend to make app purchases based on choices made under previous and similar circumstances (because of repetitive learning) related to specific environmental conditions, personal factors such as motivation, and past behavior [Bandura 1986]. The environment can affect a given user’s subconscious behavior, but specific situations can affect his or her thought, behavior, and personal perception of aspects of the environment, such as time, activity, and place [Bandura 1986; 1997]. This reciprocal determinism results in customers with different expectations each time they make a purchase.

Thus, environmental influences, such as social pressure, unique situations, cognitive effects, personality, behavior, and other personal factors interact to influence each other [Compeau and Higgins 1995b; Compeau et al. 1999]. In particular, many customers choose Web content that is based on observational learning, which decreases their trial-and-error purchasing processes [Bandura 1986; 1997]. When customers encounter favorable reviews of products or services posted by other customers, they evaluate the recommendations based on the reviewers’ similarity to themselves and their personal preferences [Lili, 2015; Benlian et al. 2012; Choi et al. 2011; Hess et al. 2009].

Outcome expectation is an important ingredient of user evaluation of PRS quality and user satisfaction with PRS in the social cognitive process [Bandura 1986]. Recommender systems that provide users with social interactions are reportedly more user-friendly and increase user comfort levels [Choi et al. 2011]. A user’s choice related to the use of PRS is reinforced by outcome expectations; these expectations comprise performance attainment and vicarious experience [Bandura 1997]. Performance attainment is based on a user’s previous experience in a similar situation (i.e., self-referencing), and vicarious experience is based on his or her observations of other people in a similar situation (i.e., social presence). Thus, the outcome expectation for users can be formed from the users’ own experiences and similar experiences of others obtained by performance attainment and vicarious experience. Outcome expectation plays an important role in explaining a user’s choice of apps.

User outcome expectations of PRS increase the usefulness of recommendations and improve user purchasing behavior [Venkatesh et al. 2003]. This way, app customers tend to prefer app stores that offer vast selections, the ability to sort and screen, and information used for evaluating alternatives and reliability. Because PRS generate outcomes for users based on their preferences and those of similar users, it is important to determine the effects of PRS social interactions in terms of understanding how users arrive at their evaluation of PRS. Based on social cognitive theory, an outcome expectation consists of a performance outcome (modeling from a previous experience) and vicarious experience (modeling from others). Thus, we consider two concepts, self-referencing and social presence, which are formed by PRS.

2.2. Mobile Recommender Systems with Self and Social Interfaces

Previous PRS studies have focused on two perspectives, such as improving PRS algorithms and user behavior, and include discussions on PRS. PRS have been developed based on a variety of algorithms, data handling, and predictive techniques [Herlocker et al. 2004]. Of these algorithms, collaborative filtering (CF) develops its targeted recommendations by considering the preferences of the user and/or similar users [Herlocker et al. 2004]. CF algorithms have been developed in various ways based on (1) the user's own content-based (i.e., item-to-item) preferences [Shani and Gunawardana 2011], (2) the preferences of other users (i.e., user-to-user) [Shani and Gunawardana, 2011; Lee and Park 2007], and (3) hybrids [Burke 2002]. These CF algorithms are widely used (Liang et al. 2007) because they are generally accurate. Most studies that aim to devise recommendation algorithms focus on increasing their accuracy by measuring the accuracy of their predictions against the actual preferences of customers [Herlocker et al. 2004].

However, self-interaction has not been considered as another type of interaction (i.e., self-referencing), although social presence has been considered an important element in terms of social interaction [Choi et al. 2011; Hess et al. 2009]. Recommender systems employed to recommend apps need to consider user self and social interactions with PRS. App store users need to make the effort of searching for proper apps. With more than one million available apps, improved search performance and better decision-making are important to customers. To this end, app stores have already installed functions related to self and social interaction environments in order to help customers find and select apps.

Self and social interactions refer to a particular form of reference communication (e.g., self, family, neighbor, and friends) that affects individual preference [Hill and Troshani 2010]. Several companies, including Amazon, Netflix, and Genius on Apple's App Store, display the following sentence to users who receive recommendations: "Recommended because you purchased (or rated).…" In addition to reducing search efforts, PRS that use self and social interactions can deliver more detailed information about the sources of recommendations that are made, and this information affects customer decision-making when considering and choosing from among the recommended items [Benlian et al. 2012; Choi et al. 2011; Hess et al. 2009; Pu and Chen 2010]. Thus, customers purchase more items and evaluate them more highly when they receive personalized recommendations compared with non-personalized recommendations [Pu and Chen 2010; Tam and Ho 2005; 2006].

From this perspective, customers consider interaction interfaces when evaluating app recommender systems [Benlian et al. 2012; Kumar and Benbasat 2006], and these interfaces are associated with the satisfaction levels and usefulness of the recommended outcomes [Wang and Benbasat 2009]. In short, based on a user's historical preference or that of other users, PRS have the ability of providing users with more information that explains a recommendation. For example, if an app recommender system uses a CF algorithm, it can list users with similar preferences as an explanation for its recommendations. Thus, the self and social interaction features of PRS can enhance customer evaluation of PRS in terms of their usefulness and satisfaction [Xiao and Benbasat, 2011].

3. Conceptual Framework and Research Model

Self and social interactions (i.e., self-referencing and social preference) can elaborate on the recommended information received from app recommender systems. When users are motivated and can pay attention, they bring logical and conscious thinking to the decision-making process. This can lead to attitude changes as users adopt and elaborate on PRS recommendations.

In addition to being based on accurate algorithms, PRS should consider self and social interaction interfaces that elaborate on their recommendations because the similarity of perceived decision processes increases user perception of the usefulness of the information. PRS that incorporate self and social interactions, and that elaborate on their recommendations, are more likely to persuade a user to make an additional purchase from among the recommended apps. Therefore, we propose a conceptual framework based on the social cognitive process [Bandura 1986] (see Figure 1).

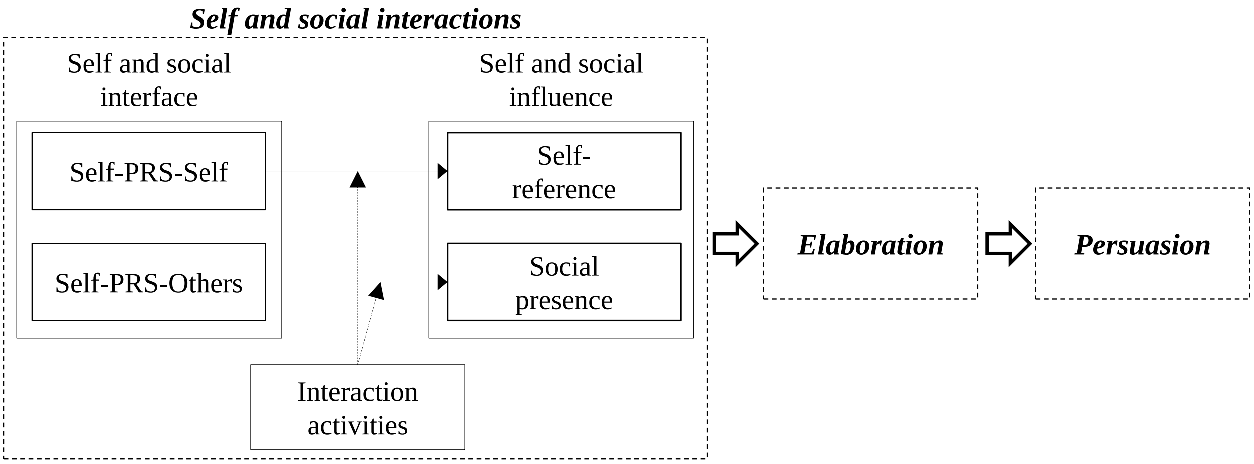


Figure 1: Conceptual Framework

Self and social interactions are defined as particular forms of reference communication that affect individual preference on PRS (i.e., informational and normative social interaction). With the two concepts of performance outcome (i.e., self-references) and vicarious experience (i.e., references from other people), individuals interact with PRS that can permit the generation of recommendations as methods for achieving self-referencing and social presence. When users obtain recommendations from PRS based on their historical references, such PRS can improve the performance outcome for users. If PRS deliver recommendations based on the preference of users and similar persons, such users can improve their vicarious experiences using PRS.

As described in Appendix 2, outcome expectation consists of a performance outcome (modeling from previous experience) and vicarious experience (modeling from others) in the social cognitive process [Bandura 1986]. Thus, there can be two types of social interface, i.e., self-PRS-self and self-PRS-other users. Self-PRS-self means that the system provides an interface with which a user can interact with his/herself through his/her previous rating data, whereas self-PRS-others means that the system provides an interface with which a user can interact with other users through the other users' previous rating data. Self-PRS-self uses historical data to generate recommendation results for individual user preferences, and provides a reason for which PRS recommend results based on the user's historical preferences. This type of PRS uses item-to-item algorithms based on the users' historical data. Thus, self-referencing recommender systems interact with a user's past preferences and generate app recommendations for the user's preference. For example, when searching for mobile apps, users expect to receive accurate results from PRS based on their past preferences (i.e., self-interaction in terms of self-reference: self-PRS-self interaction). After considering a user's past preference, self-based interaction with PRS provides good quality items to users. The results presented are in support of an advocacy from a person's careful and thoughtful consideration of the true merits of the information. In particular, the development of a personal message that is relevant to them increases user motivation for being attentive to personal messages or information. Self-PRS-self leads to self-referencing. On the other hand, self-PRS-others makes recommendations using the preferences of other by combining individual user preferences. Therefore, users feel a social presence when receiving a recommendation based on self-PRS-others.

Self and social interaction in PRS can be understood in terms of how an individual is influenced by the behavior of others with similar preferences, and also by systems that reference his or her preferences and consider similar users [Venkatesh and Brown 2001]. According to the social-interaction theory, social interaction should consider two interactions: informational and normative [Deutsch and Gerard 1955]. In this study, informational social interaction refers to the influence of accepting as evidence information that has been obtained from another comparative source. When users employ PRS to search for apps, they expect to receive from PRS accurate recommendations that reflect their preferences. In this study, normative social interaction refers to the influence of conforming to the expectations of another person or group. When users conform to normative social interaction, they feel that the group is more important and consider the opinions of similar users. Users tend to be more open to PRS recommendations when their app recommendations reflect the preferences of similar users. In short, CF usually generates recommendations using methods that are content-based and user-to-user-based. When comparing CF methods, two social interactions by PRS, social presence and self-referencing, can co-exist because of differences in the way in which CF forms its recommendations [Burnkrant and Unnava 1995]. Self-PRS-self generates results only by considering a user's historical preferences. In addition, self-PRS-others considers other preferences with the user's own. In particular, self-PRS-self interactions mean that PRS use historical preferences based on self-experiences after users provide self-information. Then, PRS consider the user's self and form self-referencing. Three algorithms in our study can reflect different methods for considering social presence (self-PRS-self by item-to-item CF), self-referencing (self-PRS-others based on user-to-user based CF), and hybrid (self-referencing and social presence based on item-to-item and user-to-user CFs). In order to identify two social interaction factors (self-referencing and social presence), we manipulate item-to-item (self-reference) and user-to-user (social presence), as described in Table 2. Thus, we verify the manipulation of our experiment settings.

After interacting with PRS from recommendations that are self-referencing and exhibit social presence, PRS elaborate on their recommendations through their perceived accuracy and novelty. These are determined by the methods used to develop recommendations (three methods in the case of CF). Thus, elaboration refers to paying attention to, and comprehending, the recommended PRS results. When PRS present detailed information related to their recommendations, the enriched information elaborates on the recommended items and simplifies a user's decision [Choi et al. 2011]. By incorporating perceived interactions, such as self-referencing and social presence, PRS can deliver to users enriched app recommendations that increase their satisfaction with PRS.

Our study focuses on an examination of how user evaluation of app recommendations affect user satisfaction and purchase decisions. Over the course of the process, there will be user evaluation and persuasion, as shown in Figure 2. Persuasion means the modification of a private attitude or belief as the result of receiving PRS recommendations. This elaboration by PRS persuades users to purchase the recommended items. The research model that incorporates self-referencing and social presence is shown in Figure 2.

In this study, we consider two parameters for PRS performance based on user perceptions: perceived accuracy and novelty. These measurements differ from predictions of accuracy and novelty for systems. In general, PRS performance is tested by calculating the error rates present in the recommendations. According to [Choi et al. 2011], user perception is important in order for users to evaluate recommender systems and the ratability of predicting metrics for PRS. Thus, a consideration of user psychological measures of app recommender systems can better influence app-purchase decision-making. Therefore, because of the user-centric context of this study, we focus on the psychological assessments made by users of recommender systems. In particular, the perceived novelty satisfies system users and increases unplanned buying of apps when PRS report the availability of items previously unknown to users. In addition to the perceived accuracy, this performance of novel recommendations is important for app recommender systems.

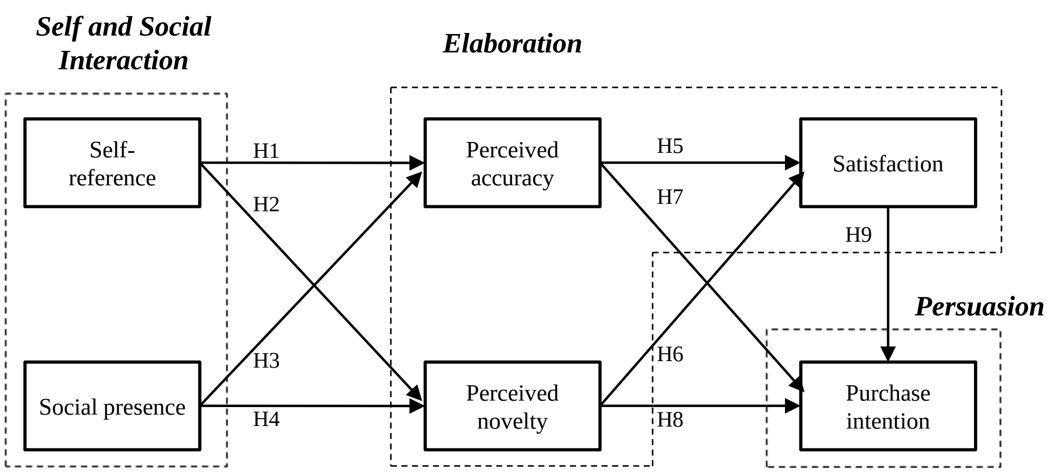


Figure 2: Research Model

3.1. Self-Referencing and Social Presence

Customers who use PRS to identify products related to their interests base their PRS evaluations on their perception of the usefulness of these tools [Bobbitt and Dabholkar 2001]. When the system proposes personalized information that incorporates user-based stimuli, its users might feel as though the system had "read their mind." Customer cognition depends on a specific context, such as the purchase of goods or use of services. Thus, on the Web, users need to be mindful of contextual cues and their experiences [Zhu et al. 2010].

Self-referencing refers to the cognitive processes used by individuals to understand incoming PRS recommendations that pertain to them by comparing such recommendations to self-relevant information stored in memory [Benlian et al. 2012; Compeau et al. 1999]. People often make decisions based on personal memories of certain meaningful experiences [Meyers-Levy and Peracchio 1996]. Thus, self-referencing is induced by giving users tasks in which they relate words or statements to aspects of themselves. PRS on the Web provide customers with meaningful self-referencing as part of their efforts to create elaborated recommendations and improve customer evaluation of the PRS [Kumar and Benbasat 2006; Tam and Ho 2006]. Many studies have described self-referencing as having beneficial effects in delivering information to users [Zhu et al. 2010]. Self-referencing can make users who want to find valuable information receive accurate information based on their preferences [Bobbitt and Dabholkar 2001; Fishbein and Ajzen 1975]. This explains why self-referencing in PRS can increase their usefulness and the likelihood of customers to follow their recommendations [Mita et al. 1993].

Previous studies related to PRS [Shani and Gunawardana 2011] have proposed that well-developed recommendation algorithms increase the accuracy and novelty of PRS, and ultimately, the results with customers. Individuals recognize the perceived accuracy and novelty of PRS when PRS provide recommendations that consider the preferences of the user or others. Although the generation of appropriate recommendations is important in the operation of PRS algorithms, users place a high value on accuracy and novelty as they perceive them [Shani and Gunawardana 2011]. Perceived accuracy represents the extent to which predicted preferences and the customers' actual preferences correspond with one another. This valuation is because users are generally unaware of the algorithm that is used and are more interested in the accuracy of the recommendations. Thus, self-referencing can improve the perceived accuracy of app recommender systems and cause customers to evaluate them more positively. This way, self-referencing can be an effective method for fostering a positive attitude toward recommendations and PRS. Thus, self-referencing increases perceived accuracy. Therefore, our hypothesis with regard to self-referencing is as follows:

***H1**: Self-referencing in PRS has a positive effect on perceived accuracy.*

Providing recommendations to users on new products or services indicates novelty or serendipity from the perspective of users [Shani and Gunawardana 2011]. Perceived novelty refers to the users' feeling on PRS performance when they learn of previously unknown items because PRS delivered novel items [Shani and Gunawardana 2011]. According to studies related to the CF algorithm, personalized recommendations with self-referencing should help users determine "newness" and use it as part of their decision criteria [Herlocker et al. 2004; Shani and Gunawardana 2011]. When users experience self-referencing that promotes elaborate PRS processing of to-be-remembered self-information, self-referencing can promote user cognition for its perceived novelty with the recommended results. That is, PRS can check an individual user's historical data, i.e., self-referencing. By checking historical data, recommendation systems can find items that a user has employed before and his or her preferences. Based on this information, recommendation systems can detect items that agree well with the user's preferences, but which have not been previously used or recommended to the person (using the item-to-item-based CF algorithm). When PRS deliver items to users, recommendation systems tend to recommend either novel or accurate items. Recommendations can be made based on the users' previous self-historical data and similar users' data, but the recommendation of repetitive and restricted items can harm the users' motivation to employ them. Users might perceive greater novelty for PRS when they receive recommendations of novel items along with explanations of self-referencing. For this reason, PRS can recommend novel items based on self-referencing. In many cases, users will not report all rating scores for all the items they have used previously. Therefore, simply improving the accuracy of PRS is not sufficient for filtering the recommendations of items already known to users [Shani and Gunawardana 2011]. The novelty of PRS is important for limiting irrelevant recommendations and notifying users of new and worthwhile items. Thus, users can feel good about the perceived novelty of PRS when they use PRS based on self-referencing. Self-referenced recommendations are based on the users' prior rating records for other items, and are not a record of their surfing. Although users can search for apps with PRS, the recommended items are generated from the users' rated preference data. Therefore, self-referenced recommendations can provide users with novel apps about which they were previously unaware. Thus, self-referencing increases perceived novelty. Therefore, our hypothesis with regard to self-referencing is as follows:

***H2**: Self-referencing in PRS has a positive effect on perceived novelty.*

Several elements on the Web can help users decide what items to buy. When users interact with other people on the Web, social presence can play a role. Social presence represents the part of the outcome expectation that influences users to consider the opinions of others with similar interests [Gefen and Straub 2004; Kumar and Benbasat 2006]. Recommendations that elaborate on the information that they contain and also incorporate social presence are important in users' decisions [Choi et al. 2011]. Furthermore, the similarity between another person and the self tends to make the other party more attractive [Aboud and Mendelson 1996]. When users want to make a choice, social presence can create a context of electronic interactions [Choi et al. 2011; Hassanein and Head, 2006; Karahanna and Limayem 2000]. This study defines social presence as the extent to which a psychological connection is formed between PRS and its users [Pavlou and Gefen 2004]. In this paper, social presence is not related to the users' social groups, such as friends. Instead, it is provided by suggesting other users with similar tastes and their preferences for items. For instance, if users receive an app recommendation and know that the outcome is based on the preference of similar users, they are more likely to evaluate the outcome more positively, and also more likely to purchase the recommended apps. Therefore, social presence affects a user's decision-making in the form of external stimuli that serve as cues [Kumar and Benbasat 2006; Tam and Ho 2005; Zhu et al. 2010]. Because PRS that use CF are based on the preferences of similar users, PRS can affect a heightened awareness of social presence, which increases the perceived accuracy of PRS [Cyr et al. 2007]. Recommendations based on similar users that also explain their procedures as a reflection of the experiences of similar users can increase their target customer perception of their accuracy [Choi et al. 2011].

H3*: Social presence in PRS has positive effects on perceived accuracy.*

According to social cognition studies, the perception of others makes individuals elaborate on information [Li et al. 2015; Khang et al. 2012]. Social presence stimulates searching by users, allowing them to obtain information about many new and unexpected products. When individuals receive novel recommendations through social presence, perceived novelty is increased if the information is new to them. As described in previous studies [Wang and Benbasat 2007], PRS can employ the preference scores of others users, which include the recommendations of other users, when providing many useful apps while decreasing the new users' search efforts. The increasing social presence of PRS can deliver apps tailored more accurately to users, but they are less helpful if the users are already aware of the suggested apps. Thus, PRS filter those items that users have already rated or to which they have previously been exposed. Items that are excluded from one user for these reasons should be considered for different users with similar user preferences. When PRS deliver novel apps to users, the novel recommendations of apps should also include information for similar users because it can enhance the target users' perceptions of novelty through their recognition that the items are unexpected and reflect the preferences of similar users. Through the use of PRS based on similar user preferences, users can receive app recommendations that are new to them and derived from the actions of similar users. Therefore, users perceive app recommender systems with a high level of social presence as being more novel.

H4*: Social presence in PRS has a positive effect on perceived novelty.*

3.2. System Performance of Personalized Recommender Systems

Previous studies have proposed that improved (in terms of accuracy) recommender systems can increase the quality of recommendations, and consequently, user satisfaction with user adoption of PRS [Al-Natour et al. 2008; Wang and Benbasat 2007]. Among the many measures for evaluating recommender systems, accuracy and novelty are the two most useful [Liang et al. 2007]. Studies have also suggested that user satisfaction increases when users perceive a recommender system as being accurate [Al-Natour et al. 2008; Liang et al. 2007]. Therefore, recommendations based on similar users that also explain that their procedures reflect the experiences of similar users can raise the sense of perceived accuracy among target customers while increasing user satisfaction with PRS [Choi et al. 2011].

H5*: Perceived accuracy has a positive effect on user satisfaction with target PRS.*

Another feature of PRS is perceived novelty, which represents the evaluation of recommendations for items about which the users were not aware [Shani and Gunawardana 2011]. Users might want to experience recommended items that are relevant, in addition to those they have not previously seen or experienced. Thus, perceived novelty needs to be considered as a factor in user evaluation of recommender systems [Fouss and Saerens 2008]. Users who receive novel messages tend to adopt the recommendations more often [Shani and Gunawardana 2011]. For example, users who receive a novel recommendation can be satisfied with the items about which they were not aware. User satisfaction does not always correlate with high recommender accuracy [McNee et al. 2002]. For example, most users might already own a specific app if that app is very popular among users. Therefore, in this case, the accuracy of a recommender system might not be effective, and simply improving the accuracy of PRS is not sufficient for filtering the recommendations for apps with which users are already familiar. The novelty of PRS is another important aspect for controlling irrelevant recommendations and providing new and worthwhile items to PRS users [Vargas 2011]. With novelty, PRS can deliver apps about which users are unaware. Thus, considering both the accuracy and novelty for app recommender systems should increase user satisfaction and the level of purchase intention for the recommended apps. Thus, novel recommendations can help users develop positive feelings about the recommender systems, and the perceived novelty can improve user satisfaction with PRS [Herlocker et al. 2004].

H6*: Perceived novelty has a positive effect on user satisfaction with the target PRS.*

PRS users can obtain accurate recommendations related to their interests using recommender systems. PRS that provide accurate recommendations make users more inclined to purchase the recommended items because the recommendations match their needs [Herlocker et al. 2004]. In addition, accurate items related to user preferences stimulate the formation of motivation of user intention to purchase. Perceived accuracy fosters a trusting belief and positive assessment toward a recommender system if its recommendations match user preferences, and such matching also increases their intention to use PRS [Choi et al. 2009]. This way, perceived accuracy influences user intention to purchase the items recommended by PRS. Novel recommendations can also help users reduce their efforts to search for new items. PRS can predict user desire in finding something new, and the novel recommendations that they deliver can increase user intention to purchase those items [Herlocker et al. 2004]. Regardless of user satisfaction with PRS, perceived novelty can increase the probability of impulsive buying because the purchase intention might increase if customers encounter unexpected and novel items [Adelaar et al. 2003; Hausman 2000].

H7*: Perceived accuracy has a positive effect on purchase intention.*

H8*: Perceived novelty has a positive effect on purchase intention.*

Satisfaction is known to be an important determinant of user attitudes, and it is an especially critical factor for products or services sold in Web stores [Hong and Tam 2006; Lee et al. 2007]. There are many aspects of customer satisfaction, and many companies want to increase it. It is clear that highly satisfactory PRS can increase their users' intention to purchase [Lee et al. 2007]. Therefore, an individual's satisfaction with a target PRS should increase his or her intention to make a transaction based on the app recommendation.

H9*: User satisfaction with target PRS has a positive effect on purchase intention.*

4. Research Methodology

4.1. Data Collection

User-based information, such as social interaction, is very important to user evaluation of PRS and for purchases of the items they recommend [Nakatsu and Benbasat 2003]. However, there is no universally accepted method for measuring user perception related to recommendations. This study aims to identify the effect of the customers' perceived accuracy and novelty on their attitude toward purchasing apps through PRS that applies two types of social interface, and in this study, this is reflected as social interaction-based influences (i.e., social presence and self-referencing). We employed apps and descriptions from Podgate (www.podgate.com), an online community in South Korea focused on smartphone apps. We selected the top 50 apps, as ranked by Apple App Store, for our experiments. We also used customer reviews for the selected apps from www.podgate.com. We conducted experiments with members of Web communities for smartphones.

In the early stages, we obtained preferences for the 50 apps from 50 early raters in order to obtain the basic preference data for all the apps, as shown in Figure 3. In general, PRS performance is reliable when a specific number of preferences (above 30 to 35 preference data) is collected [Lee and Park 2007; Herlocker et al. 2004]. These 50 early raters were then excluded from participation in the main experiment. After the preference data were collected, the participants in the main experiment were asked for their own preferences among 20 apps because CF algorithms generate recommendations based on the similarity of a user's preferences with similar users, or on his or her own ratings. CFs generate recommendations that consider the preference similarities of users for the suggested apps (i.e., social presence) [Resnick et al., 1994]. In this research, we employ user-to-user CF in order to identify users with similar tastes. This method calculates the similarities between users by employing Pearson correlations based on $r_{ij} = \frac{Cov(i,j)}{\sigma_i \sigma_j} = \frac{\sum_k (S_{ik} - \bar{S}_i)(S_{jk} - \bar{S}_j)}{\sqrt{\sum_k (S_{ik} - \bar{S}_i)^2 (S_{jk} - \bar{S}_j)^2}}$, where S_{ij} is the rating value of customer i for product j, r_{ij} is the correlation coefficient between customers i and j, and $\bar{S}_i$ is the average preference score of customer i. Unlike CF, content-based filtering is a self-referencing method for generating similar products or services by comparing user profiles and product information, such as product descriptions and features. Hybrid approaches combine collaborative and content-based filtering, either in parallel fashion to calculate prediction values or sequentially, in stages, to increase recommendation performance [Cheoh and Lee, 2008]. Each recommender algorithm examined for each group differs in its capability to generate recommendations with enriched information interfaces.

The participants in the main experiment were randomly assigned to one of six groups when they entered a starting page. These preference data from the main participants and the early raters were used to generate personalized recommendations. The main participants received and evaluated five recommendations based on their preferences after evaluating 20 items. Finally, the participants in each group were asked to complete Web-based questionnaires.

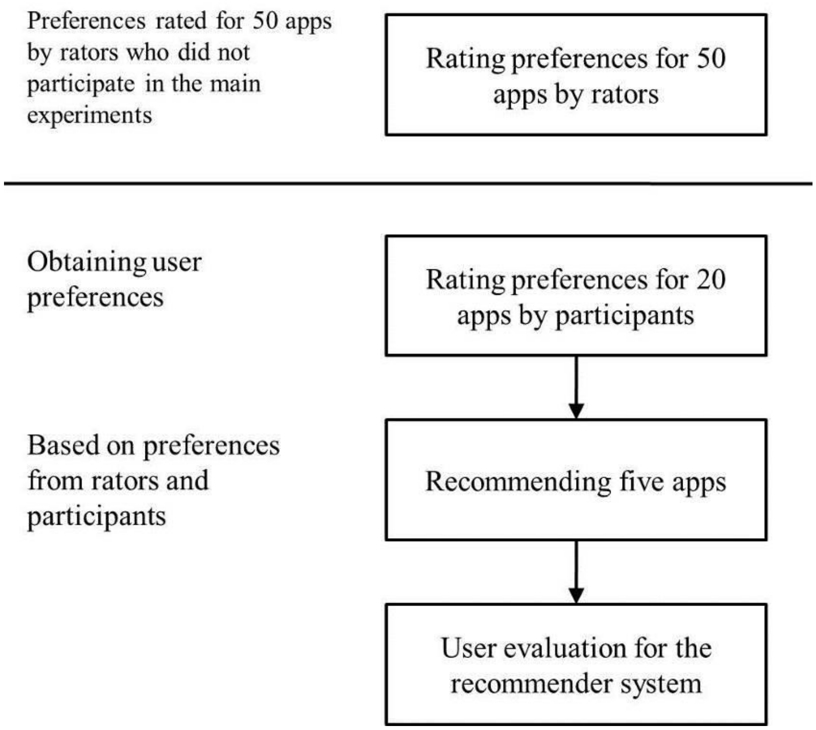


Figure 3: Data-Collection Procedure

We designed six types of experimental pages that provided app recommendations in six different ways. This was done to determine the differential effects of social presence and self-referencing on PRS, as indicated in Table 1. In order to identify two social-interaction factors (self-referencing and social presence), we manipulated item-to-item (self-reference) and user-to-user (social presence), as described in Table 2, because CF algorithms have characteristics for these factors. Thus, we verified the manipulation of our experiment settings. We used the item-to-item CF to generate app recommendations in Groups A (Appendix 3) and B based on the users' own preferences between apps [Sarwar et al. 2001]. With each recommendation for Group B, we provided an explanation for the recommendation, similar to what is provided on Amazon.com [Linden et al. 2003]. Therefore, Group B was considered to be a self-referencing group with PRS (Appendix 4).

We assigned Groups C and D as social-presence groups, and employed user-to-user CF in order to provide recommendations (Sarwar et al. 2001). To increase social presence, we provided similar user lists and made recommendations based on user-to-user CF, as explained in Appendices 5 and 7. Finally, we used a hybrid algorithm of both user-to-user and item-to-item CF to generate recommendations for Groups E and F [Burke 2002]. Hybrid CF mixed the self-referencing in Group B and social presence in Group D with the results obtained from hybrid recommendations. The PRS in Appendix 7 did not suggest explanations for recommendations. Thus, the participants in Group F were exposed to explanations that originated from both self-referencing and social presence, as explained in Appendix 8. Groups B, D, and F explained the reasons for recommendations based on how they generated the recommendations, whereas Groups A, C, and E did not provide a reason for their recommendations. Choi et al. [2011] investigated the different effects between PRS with and without explanations. Their results suggested that PRS with explanations affect user behavior more than those without explanations. Therefore, PRS without explanations were not considered in this study.

After the participants evaluated these recommendations, they completed Web-based surveys. The questionnaires were composed of 29 items with seven-point Likert scales. The measurement scales were adapted from previous studies, as explained in Appendix 9. In particular, our survey items for self-referencing are related to PRS performance. Self-referencing is related to "Relevance" (information retrieval) in the sense of how well an information-retrieval system retrieves topically relevant results. When users receive recommendations, they feel that self-referenced recommendations are the results of PRS performance. In the experiment, we showed "because you rated app _______" as a self-reference cue. Therefore, the user responded to the self-referencing of PRS performance. We adopted double-back translation methods to translate Korean survey items into English and then to Korean. Thus, we correctly managed the survey items. Appendix 10 explains the self-reference measures in comparison with the original study. Two information system (IS) researchers and one marketing researcher reviewed the survey instrument. It was then reviewed for ambiguity by a focus group of six users of app recommendation systems.

Table 1: Six Experimental Groups: Self-referencing and Social Presence

Group	Recommendation algorithm	Recommendation results
A	Item-to-item collaborative filtering	- Provide app recommendations
B	Item-to-item collaborative filtering	- Provide app recommendations - Reasons for recommendations (self-referencing)
C	User-to-user collaborative filtering	- Provide app recommendations
D	User-to-user collaborative filtering	- Provide app recommendations - Reasons for recommendations (social presence, similar users)
E	Hybrid: User-to-user and item-to-item collaborative filtering	- Provide app recommendations
F	Hybrid: User-to-user and item-to-item collaborative filtering	- Provide app recommendations - Reasons for recommendations (social presence and self-referencing)

4.2. Demographics

We recruited 156 participants from communities of smartphone users in Korea who had used more than one app from app stores. In particular, we collected most samples from teens and adults between the ages of 20 and 39 years. According to the CFI group report, almost all teens and adults between the ages of 20 and 39 years use mobile in-store apps [CFI Group, 2014; Neilsen, 2011]. Most notably, this study focuses on mobile recommender systems for app use. According to Neilsen [2011], Android users between the ages of 25 and 34 are the most active on Facebook's apps in their mobile devices (81%), followed by those between the ages of 18 to 24 years (80%), and users between 35 and 44 years (77%). In conclusion, our samples for app recommender systems are mainly teens and adults between the ages of 20 and 39 years to satisfy the purpose of our research, although older individuals can also use recommender systems.

Table 2: Participant Demographics

Group	n (%)	***Age***	n (%)	***Number of Apps purchased***	
A	25 (16.0)	Below 19	21 (13.5)		n (%)
B	24 (15.4)	20-24	58 (37.2)	0	39 (25.0)
C	26 (16.7)	25-29	50 (32.1)	1	14 (9.0)
D	25 (16.0)	30-34	20 (12.8)	2-3	23 (14.7)
E	25 (16.0)	35-39	3 (1.9)	4-5	13 (8.3)
F	31 (19.9)	40-44	1 (0.6)	6-8	10 (6.4)
		45-49	2 (1.3)	Above 9	57 (36.5)
		Above 50	1 (0.6)		
Used app category	n (%)		n (%)		n (%)
e-Books	29 (18.6)	Medical	4 (2.6)	Sports	14 (9.0)
Business	34 (21.8)	Music	74 (47.4)	Travel	16 (10.3)
Education	38 (24.4)	News	39 (25.0)	Utilities	46 (43.8)
Entertainment	117 (75.0)	Weather	36 (23.1)		
Finance	3 (1.9)	Photo	43 (27.6)	***Gender***	n (%)
Lifestyle	56 (35.9)	Reference	39 (25.0)	Male	109 (69.9)
Healthcare & Fitness	22 (14.1)	Social networking	114 (73.1)	Female	47 (30.1)

Table 2 lists the demographic information of the participants. The ages of almost all of the respondents range from teens to 34 years. According to Flurry's latest post[1], teenage groups often play free games and search for them, and those in the group of 25 to 34 years of age pay for apps. Younger players are the primary users of freemium games, downloading and playing more games than anyone else. However, the 25-34 age group, which is in the middle of the demographics, mainly pays for freemium games. Flurry commented as follows: "Sure, they're playing their share of the games, but freemium titles are almost completely funded by that stripe of the age demographic. And when you consider that the average freemium title only really pulls in-app purchases from a small percentage of its audience anyway, that age group becomes even more important." This means that the 25-34 age group has more

[1] http://flurrymobile.tumblr.com/post/113370692935/mobile-freemium-games-gen-y-plays-but-gen-x-pays

money, but not as much free time as the younger audience, and thus are willing to pay for items that help them in the game. Thus, we contend that in our experiments, the responses of the teen-to-34 age group are especially important.

We gave US $10 gift cards to use in Apple App Store as a reward to a randomly selected 10% of the participants. We described the features of PRS and our experiments to the participants. Most of the experiment participants (69.9%) were male because we recruited participants from online communities related to smartphones, mobile devices, and Mac user groups. These online communities are largely composed of males seeking information on electronics. In addition, most participants (69.3%) ranged in age from 20 to 29 years. Over 35% of the participants had purchased more than nine apps within the previous month, and the most frequently purchased apps were in entertainment, social networking, and music.

5. Data Analysis and Results

5.1. Instrument Validation

For instrument validation, we first conducted exploratory factor analysis. Three items were excluded from satisfaction (SAT1, SAT4, and SAT6) because of low factor loading and cross-loadings. We then conducted confirmatory factor analysis (CFA) using partial least squares (PLS) and SmartPLS 2.0 [Ringle et al. 2005]. The convergent validity is the extent to which variable measures act as though they were measuring underlying theoretical constructs because they share a variance [Schwab 1980]. Fornell and Larcker [1981] proposed three criteria related to evaluating convergent validity. The first is that all factor loadings must be significant and greater than 0.7. In our study, all loadings are significant and greater than 0.7, as summarized in Table 3. The second is that the construct reliability should be greater than 0.70. In our study, all construct reliabilities are greater than 0.70 (self-referencing = 0.894, social presence = 0.878, accuracy = 0.925, novelty = 0.927, satisfaction = 0.916, and purchase intention = 0.948). Finally, the average variance extracted (AVE) must exceed the variance caused by measurement error for those constructs, which means that AVE must exceed 0.50. AVE values range from 0.732 to 0.821 in our study. Cronbach's α values are also greater than 0.8 for all constructs. Thus, convergent validity is supported.

Table 3: Convergent Validity Testing

Construct	Factor loading	Cronbach's α	AVE	Construct Reliability
Self-reference (SRF)	0.708, 0.727, 0.802, 0.716	0.894	0.760	0.894
Social presence (SP)	0.771, 0.785, 0.818, 0.781	0.878	0.732	0.878
Purchase intention (PI)	0.824, 0.727, 0.800, 0.789	0.927	0.821	0.948
Satisfaction (SAT)	0.717, 0.747, 0.642, 0.613	0.878	0.733	0.916
Perceived accuracy (PA)	0.645, 0.580, 0.631,0.819	0.892	0.755	0.925
Perceived novelty (PN)	0.651, 0.779, 0.708, 0.655	0.894	0.760	0.927

Next, we examined discriminant validity, which is the degree to which the measures of two or more constructs are empirically distinct [Bagozzi et al. 1991]. Discriminant validity exists for a construct if the square root of its AVE value exceeds the square root of the correlations between that construct and the other latent variables [Fornell and Larcker 1981]. The elements shown on the diagonal in the matrix (Table 5) are the square roots of the AVEs. Table 5 indicates that all constructs have discriminant validity.

We evaluated the common method bias test (CMB test) based on several steps. First, these included appropriate instrument design and data-collection procedures proposed by Podsakoff et al. [2003]. In the second step, we tested our data for common-method variance using the Bentler and Bonnet test and Harman's single-factor test, which are steps proposed by Sharma et al. [2009] and Malhotra et al. [2006]. CMB extent was evaluated through Harman's single-factor test [Podsakoff et al. 2003]. All variables were loaded into a principal component factor analysis, and we obtained the unrotated factor solution. Six factors with Eigen values above 1 were extracted. Although one factor accounted for 44% of the total variance, we concluded that no single factor emerged from the factor analysis, and no one general factor accounted for the majority of the covariance among the measures [Podsakoff et al. 2003]. No single factor dominated the total variance, indicating a lack of CMB. In the third step, we examined CMB using the method factor whose indicators include all the principal construct indicators from previous studies [Pavlou et al. 2007; Liang et al. 2007; Podsakoff et al. 2003]. Based on the guidelines of Liang et al. [2007], we calculated each indicator's variances substantively explained by the principal construct and method factor. As described in Table 4, the average substantively explained variance of the indicators is 0.684. Williams et al. [2003] found that 46% of the variance in the indicators is accounted for by its trait factors, and 32% is accounted for by method factors on average. The average method-based variance is 0.005. If the method factor loadings are insignificant and the indicators' substantive variances are substantially greater than their method variances, CMB is unlikely to be a serious concern [Liang et al. 2007]. Considering the small magnitude and insignificance of the variance of the method—variance—CMB is unlikely to be a serious problem in this study.

Table 4: Common Method Bias Analysis

Construct	Indicator	Substantive Factor Loading (R1)	$R1^2$	Method Factor Loading (R2)	$R2^2$
Social Presence	SP1	0.779	0.607	0.026	0.001
	SP2	0.846	0.716	0.012	0.000
	SP3	0.818	0.669	-0.008	0.000
	SP4	0.765	0.585	0.013	0.000
Self-reference	SRF1	0.779	0.607	0.031	0.001
	SRF2	0.803	0.645	0.025	0.001
	SRF3	0.910	0.828	0.018	0.000
	SRF4	0.818	0.669	0.017	0.000
Perceived Accuracy	PA1	0.829	0.687	0.158	0.025
	PA2	0.810	0.656	0.161	0.026
	PA3	0.875	0.766	0.206	0.042
	PA4	0.765	0.585	0.070	0.005
Perceived Novelty	PN1	0.821	0.674	0.002	0.000
	PN2	0.892	0.796	-0.026	0.001
	PN3	0.845	0.714	0.007	0.000
	PN4	0.754	0.569	0.028	0.001
Satisfaction	SAT2	0.873	0.762	0.026	0.001
	SAT3	0.776	0.602	0.015	0.000
	SAT5	0.786	0.618	0.049	0.002
	SAT7	0.780	0.608	0.057	0.003
Purchase Intention	PI1	0.886	0.785	-0.006	0.000
	PI2	0.856	0.733	0.010	0.000
	PI3	0.901	0.812	-0.013	0.000
	PI4	0.851	0.724	0.006	0.000
Average		0.826	0.684	0.037	0.005

Table 5: Correlations among Constructs

	Self-referencing	Social presence	Accuracy	Novelty	Satisfaction	Purchase intention
Self-referencing	***0.872***					
Social presence	0.555	***0.856***				
Accuracy	0.661	0.529	***0.869***			
Novelty	0.660	0.463	0.760	***0.872***		
Purchase intention	0.618	0.472	0.589	0.674	***0.906***	
Satisfaction	0.612	0.550	0.710	0.698	0.645	***0.856***

* *Leading diagonal shows the square root of AVE for each construct*

We tested the difference between free and constraint models for perceived novelty and accuracy. If a significant model fit was generated, the discriminant validity was identified. Using this process, the x^2 difference between the pair of constructs ($\Delta x^2 = 59.774$, $p = 0.000$) was significant, and each original model had a better model fit compared with its corresponding constrained model [Anderson and Gerbing 1988]. The results indicate that the measurement model was significantly better than other alternative models. Thus, we verified discriminant validity.

5.2. Manipulation and Hypotheses Testing

This study focuses on the effects of social presence and self-referencing on the perceived accuracy and novelty of app recommender systems. We investigated these effects using experimental groups assigned different experimental pages. In order to identify the differences between the manipulated settings, we conducted analysis of variance (ANOVA). Comparisons of the differences in social presence and self-referencing among the groups are shown in Table 6. The results show that both social presence and self-referencing have significant group differences at $p < 0.00$. In terms of social presence, the values of Groups D and F that explain the recommendations indicate that for similar users, the values were greater than the values of Groups C and E. In addition, the values of self-referencing for recommendation groups with explanations (Groups B and F) were greater than the values of Groups A and E, which do not give reasons for their recommendations.

Table 6: Differences in Perceived Social Presence and Self-referencing

Dimension	Group	N	Order	Mean	S.D.	S.E.	F	Sig.	Duncan's test
Social presence	C	26	4	3.731	1.259	0.247	25.132	0.000	C=E < D < F
	D	25	2	4.950	0.984	0.197			
	E	25	3	4.040	1.133	0.227			
	F	31	1	5.766	0.398	0.071			
Self-referencing	A	25	4	4.130	1.021	0.204	4.220	0.007	A=E < B < F
	B	24	2	4.802	0.978	0.200			
	E	25	3	4.340	1.129	0.226			
	F	31	1	5.089	1.246	0.224			

Group F has the highest values for both social presence and self-referencing, and Groups C and A have the lowest social presence and self-referencing values, respectively. According to the results of Duncan's test, Groups D and F have significantly different social-presence values, and the values of Groups A and E do not differ. In terms of self-referencing, the values of Groups A and E do not differ, although the values of Groups B and F are greater than the values of Groups A and E.

Table 7: Comparisons of Perceived Accuracy and Novelty

Dimension	Group	N	Order	Mean	S.D.	S.E.	F	Sig.	Duncan's test			
									1	2	3	4
Perceived Accuracy	C	26	6	3.952	1.140	0.224	8.646	0.000	3.952			
	E	25	5	4.170	1.181	0.236			4.170	4.170		
	A	25	4	4.400	1.026	0.205			4.400	4.400		
	B	24	3	4.750	1.229	0.251				4.750	4.750	
	D	25	2	5.290	0.773	0.155					5.290	5.290
	F	31	1	5.387	0.882	0.158						5.387
Perceived Novelty	C	26	6	3.904	1.198	0.235	9.099	0.000	3.904			
	E	25	5	4.200	1.201	0.240			4.200	4.200		
	A	25	4	4.370	1.429	0.286			4.370	4.370		
	B	24	3	4.792	0.988	0.202				*4.792*	*4.792*	
	D	25	2	5.360	0.711	0.142					5.360	5.360
	F	31	1	5.468	0.942	0.169						5.468

** A: Item-to-Item; B: Item-to-Item and Explanation; C: User-to-User; D: User-to-User and Explanation; E: Hybrid; F: Hybrid and Explanation*

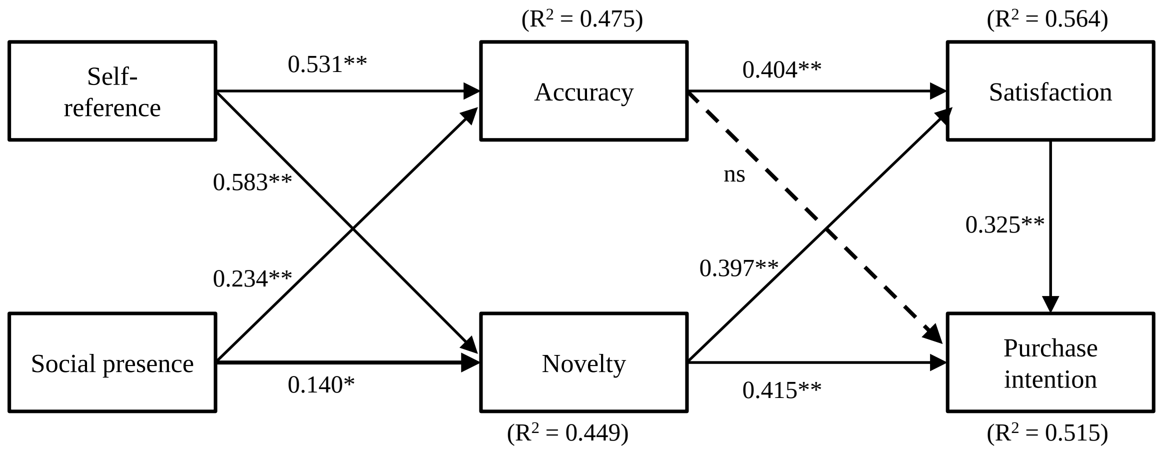
Using ANOVA, we obtained comparisons of the six groups for the different effects on perceived accuracy and novelty (see Table 7). Both the perceived accuracy and novelty of PRS differ significantly between the six groups at p = 0.01. This suggests that recommendations with explanations of their sources affect the user-perceived accuracy of the recommendations. Group B (with self-referencing), Group D (with social presence), and Group F (with both self-referencing and social presence) show greater perceived accuracy and novelty compared with non-explanation groups, such as Groups A, C, and E. Group F shows a greater perceived accuracy and novelty for both social presence and self-referencing compared with Group E (no explanation). According to the results of Duncan's test, perceived accuracy and novelty differ significantly between Groups A, C, E, D, and F.

Table 8: Comparisons of Purchase Intention and Satisfaction

Dimension	Group	N	Order	Mean	S.D.	S.E.	F	Sig.	Duncan's test		
									1	2	3
Purchase Intention	C	26	6	3.760	1.408	0.276	6.132	0.000	3.760		
	E	25	5	4.400	1.369	0.274			4.400	4.400	
	A	25	4	4.610	1.301	0.260				4.610	4.610
	B	24	3	4.990	1.131	0.231				4.990	4.990
	D	25	2	5.290	0.906	0.181					5.290
	F	31	1	5.306	1.253	0.225					5.306
Satisfaction	C	26	6	3.808	1.213	0.238	6.325	0.000	3.808		
	E	25	5	3.940	1.042	0.208			3.940		
	A	25	4	4.030	1.098	0.220			4.030		
	D	25	3	4.650	0.848	0.170				4.650	
	B	24	2	4.823	1.036	0.211				4.823	
	F	31	1	5.016	1.072	0.193				5.016	

We further tested the group manipulations of satisfaction and purchase intention using ANOVA (see Table 8). Both the purchase intention and satisfaction of PRS differ significantly between the six groups at $p < 0.01$. This suggests that recommendations with explanations of their sources affect user satisfaction for PRS and increase purchase intention for recommended items differently. Similar to the results for perceived accuracy and novelty, Group B (with self-referencing), Group D (with social presence), and Group F (with both self-referencing and social presence) have greater purchase intention and satisfaction compared with non-explanation groups, such as Groups A, C, and E. Interestingly, Group D (with social presence) can increase purchase intention better than Group B (with self-referencing). However, in terms of the satisfaction of PRS, Group B (with self-referencing) satisfies users more than Group D (with social presence). For Group F, hybrid recommendation obtains the highest scores for satisfaction and purchase intention.

We tested our hypotheses using PLS, and Figure 4 shows the results. The path coefficient for H1 (from self-referencing to perceived accuracy) is positive and significant (0.531, $p < 0.01$). Thus, H1 is supported, indicating that perceived self-referencing increases the perceived accuracy of PRS. The hypothesis for the relationship between self-referencing and perceived novelty (H2) is also supported, with a path coefficient of 0.583 ($p < 0.01$). The hypothesis that social presence increases perceived accuracy (H3) is also supported, having a significant path coefficient of 0.234. Moreover, the hypothesis that social presence increases perceived novelty (H4) is supported ($p < 0.05$). Therefore, we conclude that perceived social presence increases the perceived accuracy and novelty of app recommender systems, and that perceived self-referencing increases both perceived accuracy and novelty. The results support our hypothesis that perceived accuracy increases satisfaction (H5) with a significant path coefficient of 0.404 ($p < 0.01$). Our hypothesis that novelty increases satisfaction (H6) is also supported; its significant path coefficient is 0.397 ($p < 0.01$).



**: p< 0.05, **: p < 0.01, ns: insignificant at the level of 0.05*

Figure 4: Hypotheses Testing Results

Although the relationship between perceived accuracy and purchase intention (H7) is not significant ($p > 0.1$), the concept that perceived novelty increases purchase intention (H8) is supported by a significant path coefficient of 0.280 ($p < 0.05$). These results demonstrate the distinct, but different, roles that perceived accuracy and novelty play in satisfaction and purchase intention.

Finally, we also evaluated user satisfaction for PRS and purchase intention for app recommender systems. Our hypothesis that satisfaction increases purchase intention (H9) is supported with a significant path coefficient of 0.325 ($p < 0.01$). Our results, which are consistent with earlier studies [Jiang and Benbasat 2007; Liang et al. 2007; Thirumalai and Sinha 2009], indicate that user increased satisfaction can further increase the intent to purchase the recommended apps.

We further tested the mediation effects of satisfaction, perceived accuracy, and perceived novelty (see Table 9). Perceived accuracy partially mediates the relationship between self-referencing (SR)–satisfaction (SAT) and social presence (SP)–SAT. We also found that perceived novelty has partially mediating effects on both SR-SAT and SP-SAT.

Table 9: Mediating Effects obtained for Satisfaction, Perceived Accuracy, and Perceived Novelty.

	Path Test						Sobel test	
Mediator	Path	Path Coefficient	S.D.	S.E.	t-value	Sig.	z-value	Sig.
Satisfaction (SAT)	PA → PI	0.043	0.079	0.079	0.545	n.s.	2.749	0.006
	SAT → PI	0.325	0.079	0.079	4.092	p<0.01		
	PN → PI	0.375	0.124	0.124	3.037	p<0.01	2.439	0.015
	SAT → PI	0.325	0.079	0.079	4.092	p<0.01		
Perceived Accuracy (PA)	SR → SAT	0.166	0.067	0.067	2.479	p<0.01	2.729	0.006
	PA → SAT	0.363	0.127	0.127	2.866	p<0.01		
	SP → SAT	0.139	0.062	0.062	2.241	p<0.01	2.303	0.021
	PA → SAT	0.335	0.114	0.114	2.930	p<0.01		
Perceived Novelty (PN)	SR → SAT	0.166	0.067	0.067	2.479	p<0.01	2.581	0.010
	PN → SAT	0.313	0.118	0.118	2.653	p<0.01		
	SP → SAT	0.215	0.053	0.053	4.039	p<0.01	2.847	0.004
	PN → SAT	0.313	0.118	0.118	2.653	p<0.01		

We compared the path of perceived accuracy and novelty to satisfaction using PLS regression (PLS-R) with variable importance by conducting xlstat-PLSPM. We combined both PLS-R and the variable importance in projection (VIP) score for variable selection in order to estimate the contribution of each variable to the model [Tran et al. 2014; Zuber and Strimmer 2010]. The advantage of using a model-based approach is that it is more closely tied to model performance. In addition, by doing so, we can incorporate the correlation structure between the predictors into the importance calculation.

We examined the variable importance to determine which variables contribute statistical significance to the model. The variable importance measure is based on the weighted sums of the absolute regression coefficients [Green et al. 1978]. The weights are a function of the reduction of the sums of squares across the number of PLS components, and are computed separately for each outcome. Therefore, the contribution of the coefficients is weighted proportionally to the reduction in the sums of squares. To examine different contributions of variables to the dependent variable, the variable importance uses the squared semi-partial correlation [Tran et al. 2014]. If the predictors are correlated, the squared semi-partial correlation represents the unique variance explained by a given predictor. Semi-partial correlation refers to the unique contribution of a factor to the model (i.e., the relationship between the dependent variable and predictor after the contributions of the other predictors have been removed from the predictor). In this case, the sum of the squared semi-partial correlations is less than R^2. This remaining explained variance represents the variance explained by more than one variable. Table 10 describes the impact and contribution of both variables to SAT. We consider that the satisfaction is well explained ($R^2 = 0.564$). The result shows that perceived accuracy has a greater effect on satisfaction than perceived novelty. Table 10 summarizes the preceding results. In order to calculate the contribution of each independent variable, the correlation between the independent and dependent variables multiply independent's path coefficient. The contributions of perceived accuracy and novelty are 0.287 and 0.277, respectively. We see that perceived accuracy has a 51% contribution to R^2. In addition, the effect of perceived novelty on satisfaction is a 49% contribution to R^2. Figure 5 illustrates the information presented in the tables. Thus, we contend that both perceived novelty and accuracy are important factors for user satisfaction.

Table 10: Contributions of Perceived Accuracy and Novelty to Satisfaction.

	Perceived Accuracy	Perceived Novelty
Correlation	0.711	0.698
Path coefficient	0.404	0.397
Correlation * path coefficient	0.287	0.277
Contribution to R^2 (%)	50.863	49.137

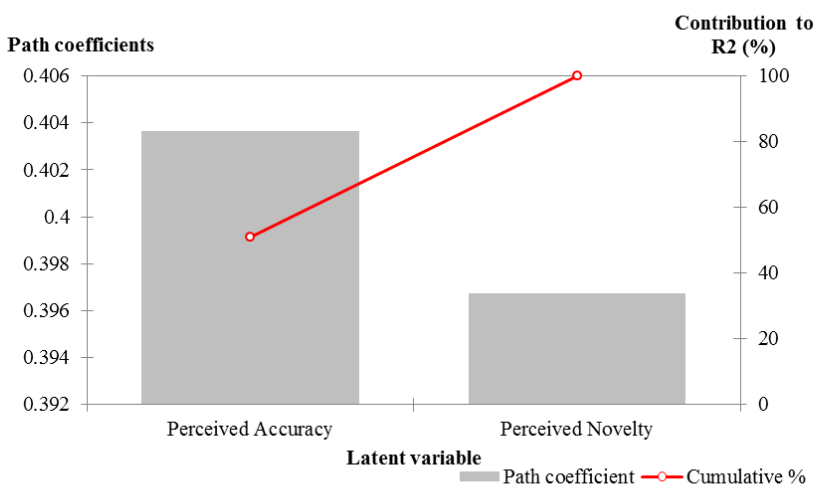


Figure 5: Impacts of Perceived Accuracy and Novelty on Satisfaction

6. Discussion and Implications

6.1. Discussion of Findings

This study identifies how an app recommender system based on the social cognitive process can provide user-friendly recommendations that increase customer satisfaction for PRS and purchase intention. The results confirm the effectiveness of including two types of self and social interaction-based influence (social presence and self-referencing) when customers search for apps. Although PRS were examined using similar user lists and self-referencing information for item preferences, they were more effective when they included social presence and self-referencing.

Our results further identify the roles of social presence and self-referencing as predictors of the perceived performances of PRS in terms of characteristics such as perceived accuracy and novelty; these results are consistent with previous research [Arazy et al. 2010]. Thus, app recommender systems, including those that incorporate social presence and self-referencing, increase user evaluation of the perceived performance of recommender systems. In contrast, previous studies have not considered self-referencing. This study examines the effect of self-referencing from PRS and confirms its importance in addition to social presence. In particular, we found that self-referencing is important in relation to how users evaluate PRS performance with the recommendation of accurate and novel apps. Self-referencing increases user evaluation of PRS, although previous studies have suggested that social presence can be used to evaluate PRS performance [Choi et al. 2011; Hess et al. 2009]. Similar to the findings by Zhu et al. [2010], our results indicate that by incorporating interfaces and socializing cues into app recommender systems, we can increases the users' sense of social presence based on information from vicarious experience. In addition, individual preference rating scores improve self-referencing in PRS. Furthermore, the use of the hybrid approach of combining Groups B and D is superior to using either Group B or Group D alone as a way of increasing social presence and self-referencing. Hybrid recommendations that combine algorithms, such as user-to-user CF or item-to-item CF, might improve recommender systems [Burke 2002]. These results demonstrate that the PRS algorithms examined in this study differ in their ability to generate outcomes with enriched self and social interaction-based interfaces.

The results also show the superiority of personalized app recommender systems that use socializing interfaces over those that lack them. Those that incorporate them increase user elaboration, such as perceived accuracy and novelty, in outcome recommendations [Xiao and Benbasat 2007]. More interestingly, similar-user lists and self-statements are most effective with hybrid recommender systems, and they increase perceived accuracy and novelty. However, recommendations given without providing the recommending reasons do not increase either of these, and do not differ in their evaluations of perceived accuracy and novelty (Groups A, C, and E), although these groups deliver recommendation outcomes based on different algorithms. In other words, personalized app recommender systems without explanations do not improve the users' perceived performance of app recommender systems. PRS can also ensure that they generate accurate and novel outcomes by taking care to base their recommending algorithms on the users' individual information. These accurate and novel apps increase a user's expectation that he or she will have received from PRS recommendations of relevant apps available in app stores.

Previous studies have focused on improving PRS algorithms based on predictive measures, such as precision and recall [Herlocker et al. 2004]. However, this study, which is based on a user-centric evaluation perspective, proposes that perceived accuracy and novelty are related to perceived PRS performance. Our findings are consistent with previous studies that propose that social presence results in higher quality recommendations and improves user attitudes. Thus, app recommender systems with social presence can improve the attitudes of users when searching for apps. In addition, user-perceived novelty of the recommended items is based on a user's individual preferences [Shani and Gunawardana 2011], and thus app recommender systems with social presence and self-referencing increase perceived novelty using the app preferences of similar users [Gefen and Straub 2004; Wells et al. 2011]. In summary, this study has described the social cognitive process that affects how self and social interactions elaborate on user evaluation of perceived performances (perceived accuracy and novelty) in app recommender systems. Although previous studies have improved the prediction measures of PRS performance (precision and recall), we measured the perceived concept of novelty and accuracy. Our findings confirm the importance of perceived accuracy and novelty by showing their significance when users search for apps in app stores. In particular, our result indicates the importance of perceived novelty and accuracy in recommender systems. There is increased user satisfaction by customers pleased with receiving novel and accurate items from recommender systems. Thus, we contend that customers evaluate recommender systems based on the perceived novelty and accuracy of app recommender systems.

In addition, we found that perceived accuracy increases user satisfaction with app recommender systems, but does not significantly increase purchase intention because of the role of perceived accuracy in fully mediating the relationship between "self-referencing–satisfaction" and "social presence-satisfaction." Accurate items do not always correspond to new items (i.e., app recommender systems can also have the potential of delivering apps with which users are already familiar from other sources). This suggests that user perception of PRS accuracy only indirectly affects purchase intention as a factor in increasing their degree of satisfaction with PRS.

We also found that perceived novelty partially mediates the relationship for both "self-referencing-satisfaction" and "social presence-satisfaction." In addition, perceived novelty can directly affect purchase intention. For example, if users acquire novel apps from PRS based on their preferences, and were previously unaware of these apps, the perceived novelty for PRS could give users the opportunity of making impulsive app purchases [Hausman 2000]. Furthermore, when they receive novel app recommendations related to their preferences, they might also become satisfied with PRS. The definition of a psychological impulse is described as "a strong sometimes irresistible urge; a sudden inclination to act without deliberation" [Rook 1987]. Another possibility arises because almost all our respondents range in age between 20 and 29 years. In general, younger people are more likely than older individuals to purchase new and challenging items. Therefore, there could be a direct relationship between perceived novelty and purchase intention.

Interestingly, we found that perceived novelty directly increases PRS satisfaction and purchase intention. Although previous studies have focused on PRS accuracy, our results suggest that perceived novelty can be another important factor for PRS user satisfaction. Novelty from PRS is a highly desirable feature for recommendation. For most intentions, the purpose of recommendation is inherently linked to a notion of discovery that the user might not have found alone (i.e., PRS accuracy). Considering the result of perceived novelty to satisfaction, perceived accuracy has the inability of capturing the broader aspects of user satisfaction in existing systems [McLaughlin and Herlocker, 2004]. In order to increase user satisfaction and purchase intention, recommendations should provide novelty and accuracy. This means that user satisfaction with recommender systems is related not only to how accurately the system recommends, but also to how much it supports the user's decision-making based on generating novel items. When users acquire novel apps generated from app recommendation systems, such users might then want to purchase the apps. In addition, although accurate results increase user satisfaction with PRS, user purchase intention could not be affected without satisfaction with PRS, which delivers successful impulsive outcomes. Recommender systems with accuracy can increase the users' benefit of searching for apps in app stores. However, perceived accuracy does not always support purchase decision-making because accurate recommendations are generally related to user-interest predictions that involve inherent uncertainty based on incomplete evidence of interests [Zhang, 2013]. Perceived accuracy is more related to the satisfaction of recommender systems to not immediately purchase products.According to the results, the research for recommender systems should consider perceived novelty for increasing the user's purchase decision-making. Because the perceived novelty of app recommender systems increases both user satisfaction and intention to purchase apps, recommender systems should deliver novel and accurate app recommendations in order to increase user satisfaction and purchase intention.

6.2. Limitations and Future Direction

The results of this study should be interpreted in the context of its limitations. First, the results are limited to the context of apps. This might suggest that users evaluate different product types differently. In particular, there are different perspectives to the perceived accuracy and novelty of app recommendations because apps pose a low risk to the users' decision-making. Therefore, a wider variety of product types and information sources with high costs should be compared with the results in this study. Second, the apps used in our experiments span all categories that exist in Apple App Store. However, most app store sales belong to recreational categories, such as entertainment, social networking, and music. Third, the participants in this study were from Korea, and the results might differ in other countries because of different types of network infrastructures and cultural values. In addition, in future work, we should consider all age groups by focusing on categories related to older age groups. Recently, consumers of all ages have begun to utilize services on their mobile devices, although most consumers who use such devices range in age from 20 to 29 years [Salesforce 2014]. According to previous studies [CFI Group, 2014; Neilsen, 2011], this study focuses on teens and adults in the 20–35 age group. It is expected that individuals in older age groups would participate more if the research were to focus on app categories that appeal to the interest of such older individuals, such as the life and health app categories. Third, our experiment was based on scenario-based manipulation. To improve realism, random samples and data should be obtained in real situations. Furthermore, our experimental systems did not consider privacy issues related to user information in order to generate recommendations. In practice, managers should carefully consider how to control the privacy of their users who employ recommender systems. Future studies should consider detailed app categories and compare high and low-involvement products. Although this study was limited in scope, we hope that greater effort will be devoted to this important research area, and that the proposed model will serve as a useful guide for such future work.

6.3. Implications for Research and Practice

The primary contribution of this study extends social-cognitive theory in the field of personalized app recommender systems by considering self and social interactions. In order to identify the self and social interactions of PRS, performance outcomes and vicarious experience were used to identify self-referencing and social presence in app recommender systems. In addition, we employed both informational and normative social interaction to explain the perception of self-referencing and social presence in PRS. Therefore, this study extends the self and social interactions of PRS in terms of social-cognitive theory.

In this study, we identified four important implications that are theoretically related to the use of PRS in order to extend the social-cognitive process and allow a better understanding of user purchase intention. We assessed the effectiveness of self and social interactions (self-referencing and social presence, respectively), measured the perceived accuracy and novelty in users that evaluate PRS perspectives, and ascertained the differences in their effectiveness in terms of their assessment of perceived accuracy, perceived novelty, and satisfaction.

First, this study extended the social-cognitive process by applying it to the field of PRS, especially self and social interactions (i.e., social presence and self-referencing), elaboration (i.e., perceived novelty, perceived accuracy, and satisfaction) of app recommender systems, and persuasion (i.e., purchase intention). This study helps bridge a gap in research and the literature by explaining the role of the social-cognitive process, and the effectiveness of self and social interaction factors in the use of app recommender systems. Similar to the findings of Wells et al. [2011], this study showed that social interaction-based influence factors increase user cognition of PRS quality in terms of their elaborated perceptions, such as perceived accuracy and novelty. Moreover, positive perceptions of PRS performance influence user satisfaction [Wells et al. 2011] and persuade users to purchase the PRS recommended apps.

Second, in order to increase user evaluation of social interactions and perceived performance, it is very important for PRS to deliver recommendations that incorporate explanations. In particular, in this study, we found that self-referencing increases user cognition related to the suitability of the recommendations to social presence [Hess et al. 2009; Zhu et al. 2010]. As indicated in Table 8, recommendations with personalized reasons that use social presence and self-referencing lead users to increase their positive evaluation of PRS quality in terms of perceived accuracy and novelty. However, this is not true of users who received recommendations without personalized reasons. This finding is in good agreement with those of previous studies [Arazy et al. 2010; Wells et al. 2011]. Based on our results, it is apparent that social presence and self-referencing are important sources of the perceived accuracy and novelty of PRS. Therefore, practitioners should understand the importance of designing PRS with social interaction factors and the importance of improving the performance of PRS algorithms.

Third, this study measured the perceived accuracy and novelty of recommender systems in order to understand user perceptual evaluation of PRS. Previous studies have focused on how the use of accuracy to decrease errors in PRS algorithms also affects the performance of recommender systems [Shani and Gunawardana 2011] with precision and recall measures; however, this study found how to deliver and measure the roles of perceived novelty in PRS evaluation. When users evaluate PRS, they equally use their perceptions of its accuracy and novelty in forming an opinion of the system's performance. This study also confirmed previous studies on improving algorithms for recommender systems [Herlocker et al. 2004], which concluded that user-based perceptual measures, such as perceived accuracy and novelty, can ultimately cause higher PRS evaluation.

Fourth, we identified the mediating effects of three mediators (satisfaction, perceived accuracy, and perceived novelty). As discussed earlier, the importance of perceived accuracy lies in its contribution to user satisfaction, which in this study is directly linked to user purchase intent, and according to Herlocker et al. [2004], to better evaluations of recommender systems. However, perceived novelty is a factor in both satisfaction and intent to purchase as a mediator. Perceived accuracy functions in convincing users that PRS can simplify their search-related problems, and this way, perceived accuracy contributes to satisfaction; however, perceived novelty goes further by arousing user interest with information, services, and products that are new to them. This does not imply that PRS do not contribute anything to the intention to purchase. This added interest not only adds to user satisfaction with PRS, but also increases their intention to purchase and adds to their impulsive buying [Hostler et al. 2011]. In summary, recommender systems should ensure that they include both accuracy and novelty in their recommendations as a method for improving user evaluation of these systems and their satisfaction with PRS [Shani and Gunawardana 2011]. The demonstrated importance of these factors illustrates why online app stores should ensure that their recommendations are not only accurate, but also incorporate novelty.

This study also has important practical implications. First, it provides new insights to companies that sell apps on the Web and mobile devices with regard to strategies that can improve their delivery of suitable apps and increase their sales. Sales of mobile apps are a key revenue source in the mobile app economy (Kim et al. 2016). The sustainability of social media services is often plagued by their insufficiency (Kim et al. 2015). Managers can benefit by devising the delivery of recommendations that use social cues, such as social presence and self-referencing. Recommendations that incorporate more information might cause users to give higher evaluations and increase their purchase intentions. This can improve their expectations when using recommender systems and purchasing apps. Therefore, in developing their recommender systems, corporate managers need to go beyond merely focusing on the performance of their algorithms, and should recognize the importance of social presence and self-referencing. In particular, developers should include the social context of their app content. This is particularly important when delivering novel recommendations that increase user purchase intentions.

Second, although perceived accuracy only increases user satisfaction, perceived novelty is also directly related to the intention to purchase recommended apps. Capitalizing on this advantage conferred by perceived novelty can give app venders a competitive advantage by increasing the possibility of impulse buying by their customers [Adelaar et al. 2003]. Thus, PRS designers should attempt to deliver novel recommendations in order to increase user satisfaction with PRS and their intention to purchase.

Third, the experiments employed in this study were conducted solely with app recommendations. Although the social-cognitive process appears to be an important avenue for increasing user evaluation of recommender systems, care should be taken with respect to the types of products under consideration, such as whether they are utilitarian versus hedonic, or tangible versus intangible. Thus, companies should consider which products or services are successful when using PRS. Although this study did not use any specific features of mobile apps, such apps are available for both mobile and desktop environments from sources such as Apple App Store on iTunes and the Web Store of the Chrome browser. Therefore, the results of this study can be generalized in personalized recommendations to deliver products suitable to users.

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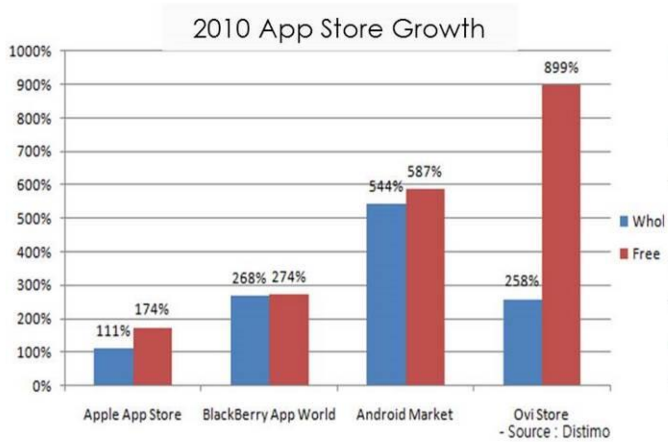
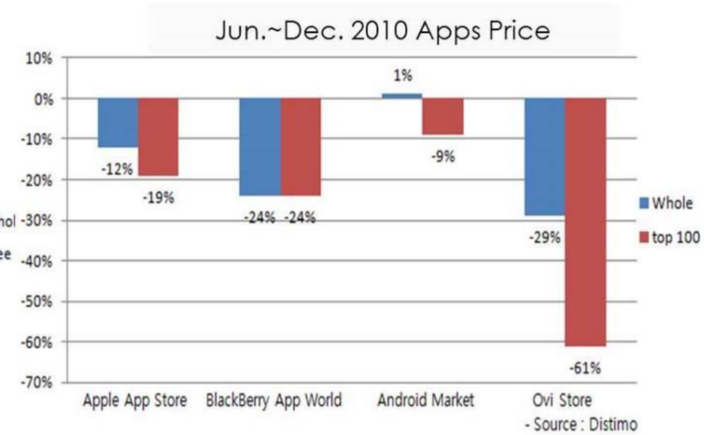
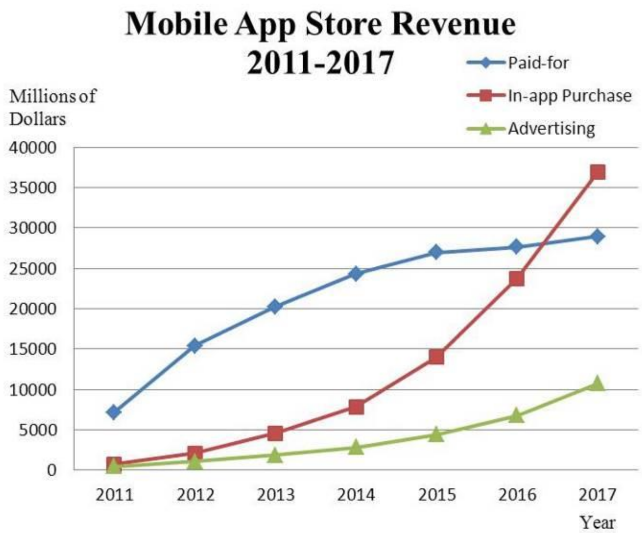
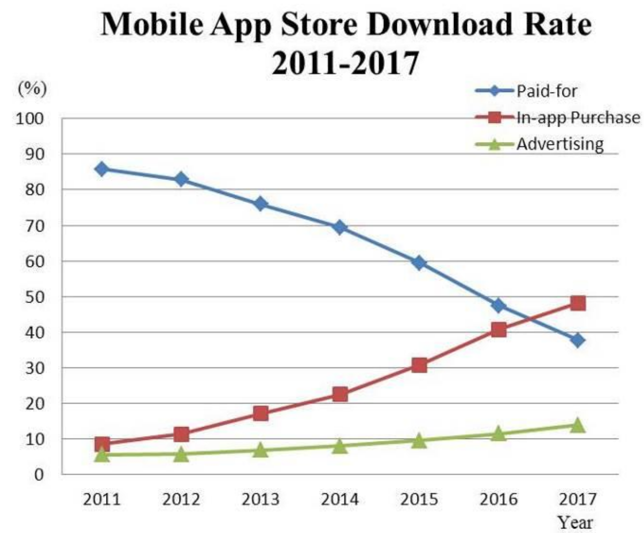
Appendix 1. App Store Growth and Revenues (Gartner 2013)

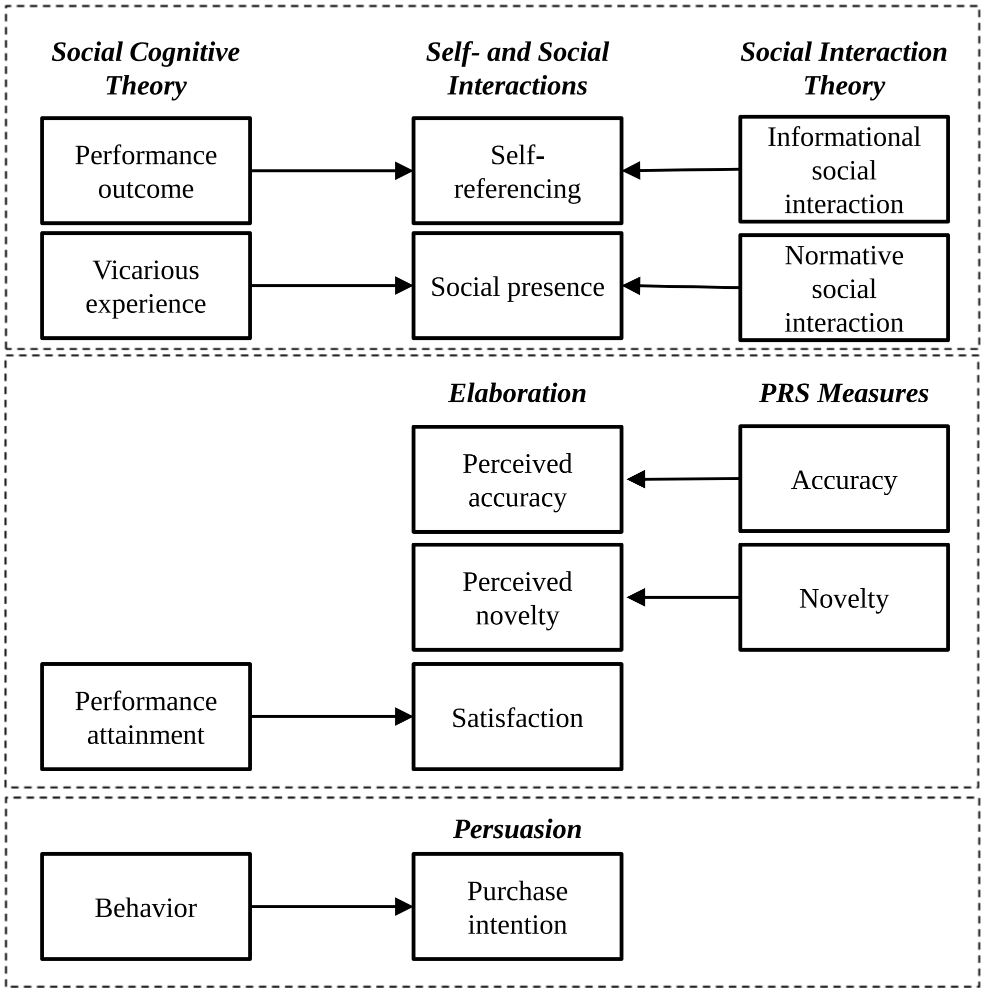




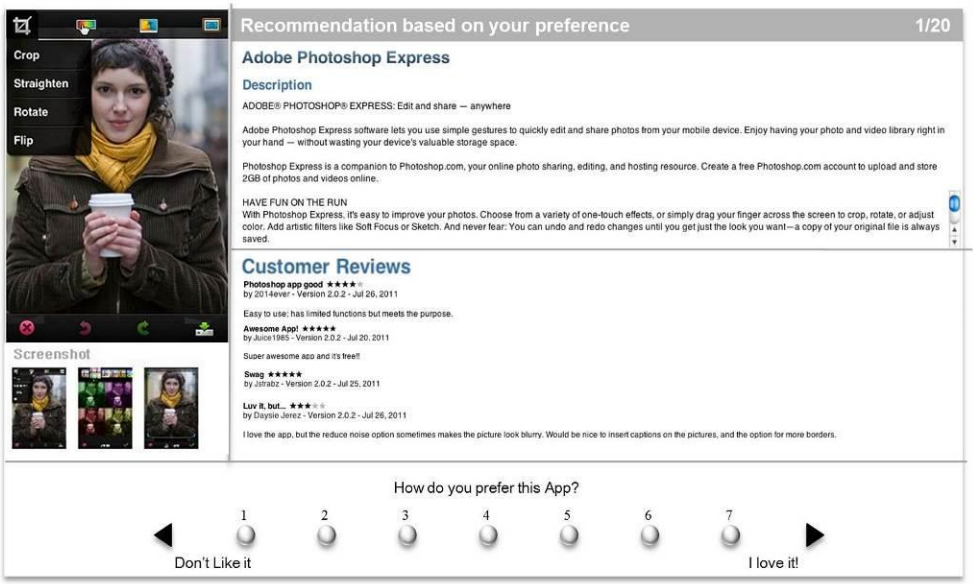




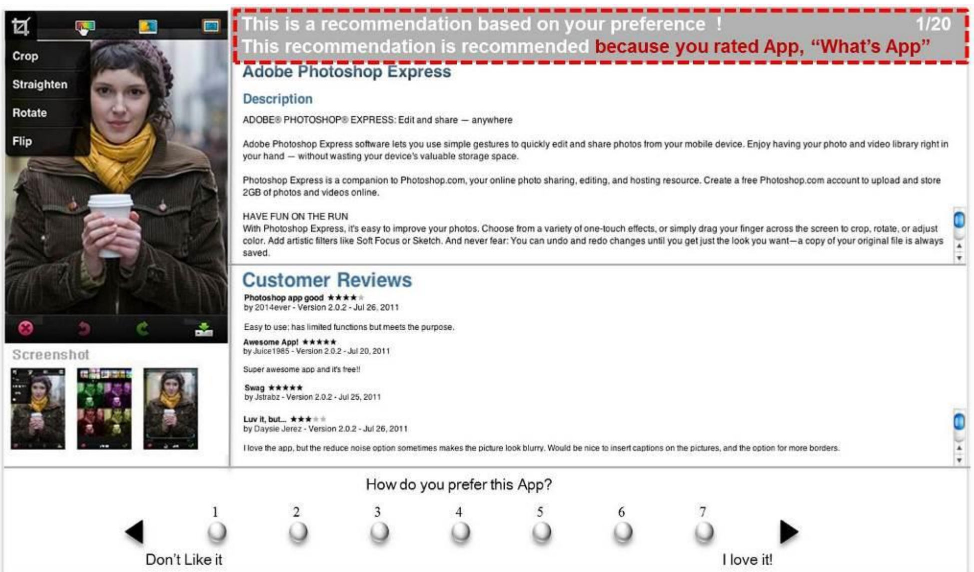
Appendix 2. Conceptualization for Theoretical Development



Appendix 3. Recommendation from Item-to-Item Collaborative Filtering (Group A)[2]

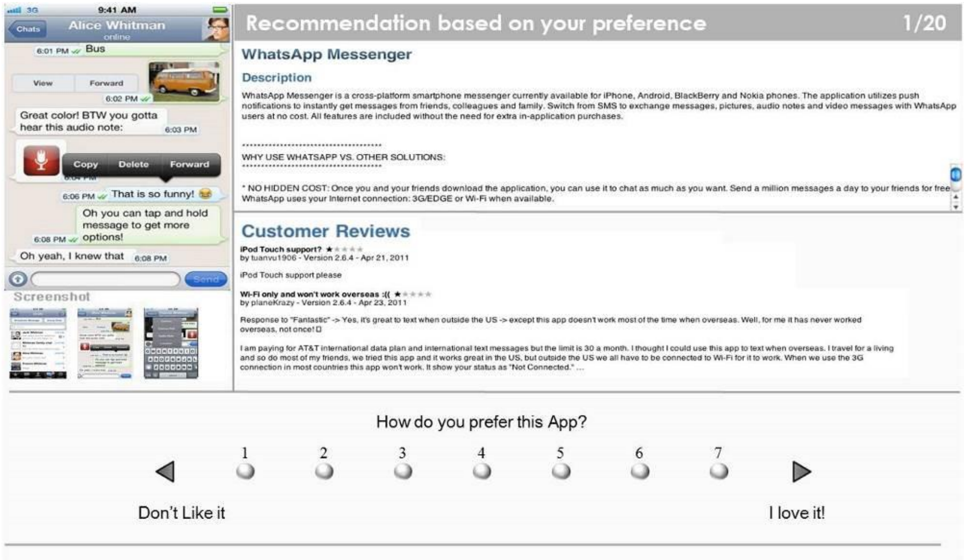


Appendix 4. Recommendation from Item-to-Item Collaborative Filtering with Self-referencing Sentences (Group B)

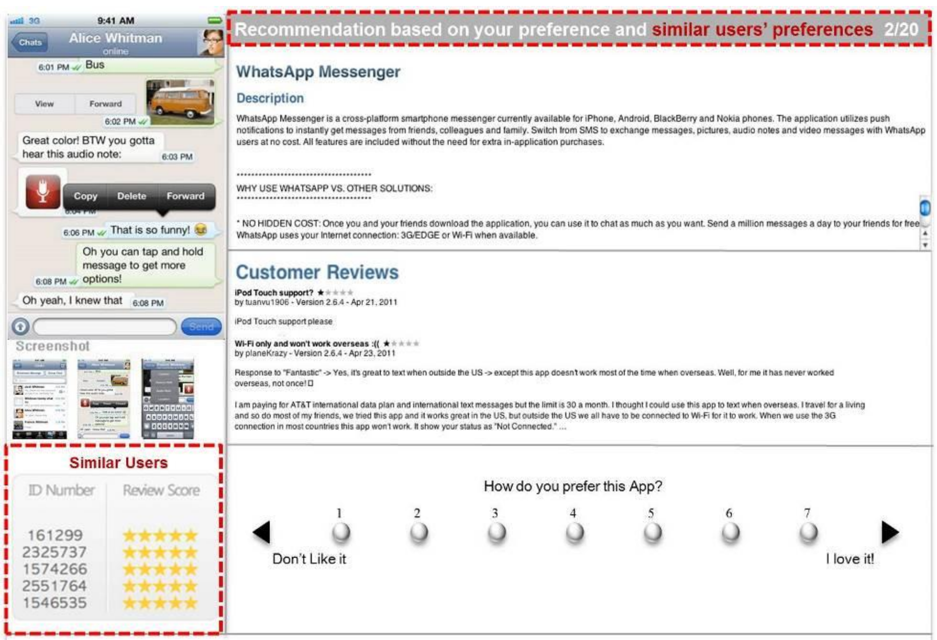


[2] The photograph of a woman used here was selected from a Photoshop app. Because this photo is neither a recommending agent nor the photo of a similar user, we do not consider it to have any effect on social presence. In other words, the photographs in the appendices are merely advertising for Adobe Photoshop, and are unrelated to the users' perceived social presence in app recommender systems. App recommender systems that want to increase social presence for users can deliver pictures of similar users or friends. Presenting images of similar users to users can be an additional way of adding an element of interaction.

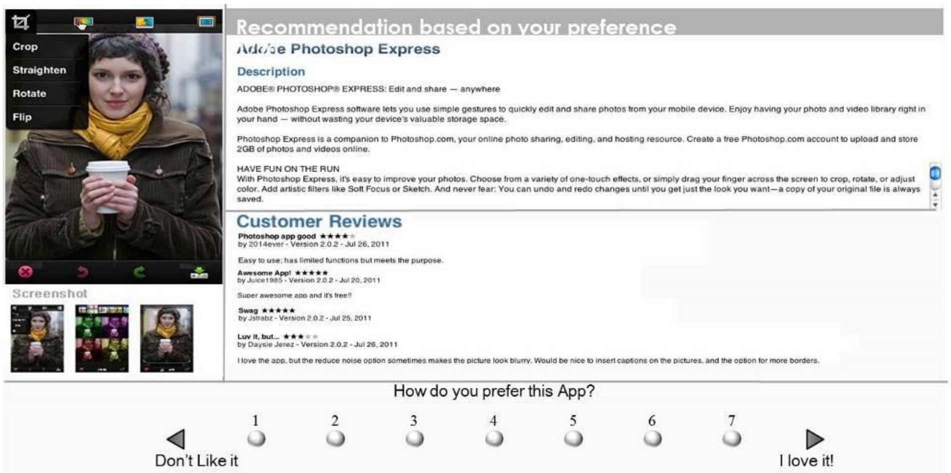
Appendix 5. Recommendation from User-to-User Collaborative Filtering without A Similar User List (Group C)



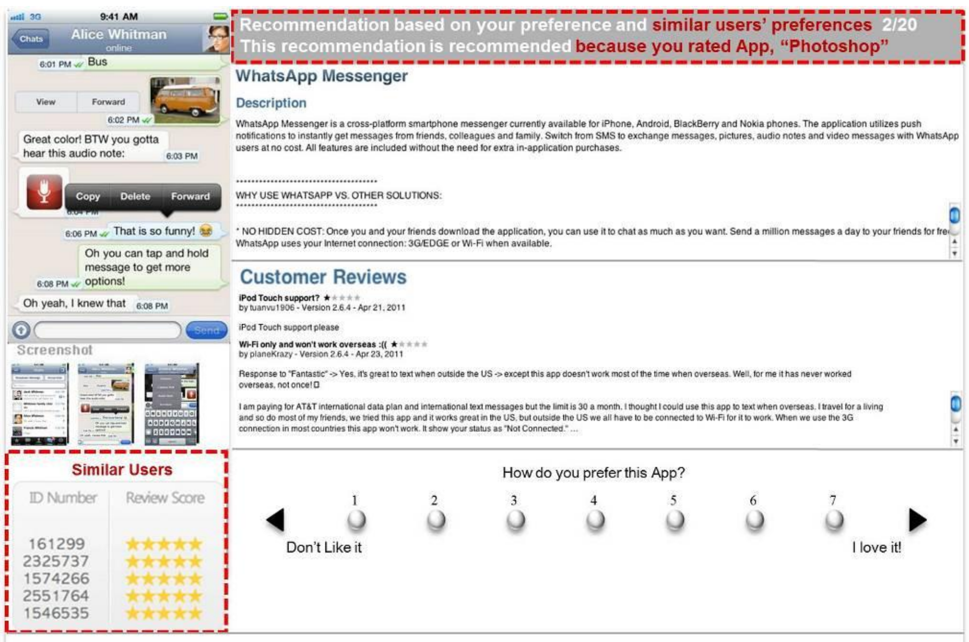
Appendix 6. Recommendation from User-to-User Collaborative Filtering with A Similar User List (Group D)



Appendix 7. Recommendation from Hybrid Filtering without A Similar User List and Self-referencing Sentences (Group E)



Appendix 8. Recommendation from Hybrid Filtering with A Similar User List and Self-referencing Sentences (Group F)



Appendix 9. Measurement Instrument

Constructs	Items	Wording	References
Self-reference (SRF)	SRF1	The recommended items from PRSs relate to me personally.	Burnkrant and Unnava (1995)
	SRF2	I am reminded of myself with recommended items from PRSs.	
	SRF3	I think the recommended items from PRSs reflect me.	
	SRF4	I believe that the recommended items from PRSs seem to be generated with me in mind	
Social presence (SP)	SP1	There is a sense of human contact in the recommender system.	Gefen and Straub (2004)
	SP2	There is a sense of human warmth in the recommender system.	
	SP3	There is a sense of personality in the recommender system.	
	SP4	There is a sense of human sensitivity in the recommender system.	
Perceived accuracy (PA)	PA1	Recommended Apps are suitable for my interest.	Xu (2006)
	PA2	Recommender system is a good source for my decision to choose Apps.	
	PA3	Recommender systems provide the recommended results I need.	
	PA4	Recommender systems provide Apps appropriate to me.	
Perceived novelty (PN)	PN1	Recommender system offers new Apps for my preference.	Moorman (1995)
	PN2	Recommender system offers new Apps for my interested App category.	
	PN3	Recommender systems satisfy my sense of curiosity.	
	PN4	Recommended Apps are familiar to me.	
Satisfaction (SAT)	SAT1*	This recommender systems is one of the best systems I could have used	Dawes et al. (1998)
	SAT2	The recommender systems I used are as good as I expected.	
	SAT3	I am not dissatisfied with the service provided from recommender systems.	
	SAT4*	My choice to use this recommender system was a wise one.	
	SAT5	This recommender system provides exactly what I need.	
	SAT6*	I am satisfied with my decision to use provided recommender systems.	
	SAT7	My choice to use this recommender system was appropriate.	
Purchase intention (PI)	PI1	I intend to purchase Apps through this recommender system.	Pavlou and Gefen (2004)
	PI2	Given the chance, I intend to buy Apps with this recommender system.	
	PI3	I think it is positive to buy the recommended Apps through this recommender system.	
	PI4	It is likely that I will actually purchase Apps from this recommender system.	

* These items were dropped after the exploratory factor analysis.

Appendix 10. Measures Comparison

Measure	Original items	Ours
Self-referencing	Burnkrant and Unnava (1995) -What it would be like to use the calculator -I was reminded of my own experiences with calculators -I believed that the ad seemed to be written with me in mind -I believed that the ad related to me personally.	- The recommended items from PRSs relate to me personally. - I am reminded of myself with recommended items from PRSs. - I think the recommended items from PRSs reflect me. - I believe that the recommended items from PRSs seem to be generated with me in mind.