INCORPORATING USER PERCEPTIONS AND PRODUCT ATTRIBUTES IN SOFTWARE PRODUCT DESIGN AND EVALUATION

Completed Research Paper

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Abstract

In order to better explain and predict consumers’ preferential choices of software products, we propose an integrated reconceptualization of IT that incorporates the tool, proxy and ensemble views of IT. We also develop a choice-based conjoint model to incorporate the product attributes, external control factors, user perceptions, and contextual factors to estimate users’ software preferences. The influences of product attributes on users’ perceptions of product characteristics are also examined. With a choice-based conjoint study, and the collection of additional data on users’ perceived product characteristics, we demonstrate that the proposed model can better explain and predict users’ software choices than the model with product attributes or with user perceptions exclusively, in terms of the in-sample fit and the holdout prediction hit rate at the individual-level and the aggregate-level. This study contributes to the literature by providing a better understanding of how various IT components jointly determine consumers’ software selection decisions.

Keywords: software selection decision, software design, choice-based conjoint analysis, conceptualization of IT, hierarchical Bayesian
Introduction

Consumers often choose software products on the basis of essential attributes, such as price, functionality, and vendor support. To improve product differentiation and meet consumers’ needs better, vendors must understand the key drivers that affect consumers’ software product choices. Central to software design is determining an optimal combination of product features that appeals to the target market (Lucas et al., 1988; Carmel and Sawyer, 1998). This study focuses on mobile applications (apps), which we consider as a new category of software. Mobile apps are becoming increasingly common; their the unique constraints of handheld devices (e.g., small screen size and limited memory) pose new design challenges (Adipat et al., 2011). However, effective design of mobile user experience has received limited attention.

Different methods have been applied to guide software product design. For example, technology acceptance model (TAM, Davis 1989) is specifically developed for explaining and predicting user technology adoption behavior (Chau and Hu, 2001; Venkatesh, 2000); it emphasizes the important roles of perceived usefulness and ease of use. In contrast to user perceptions, conjoint analysis (Green and Rao, 1971; Green and Srinivasan, 1990; Louviere and Woodworth, 1983) models consumer choice as a function of product attributes; typically, it measures the importance that consumers place on different product attributes and use those measurements to make design trade-off decisions (Feit et al., 2010). These two streams of research represent distinct and probably complementary ways to conceptualize information technology (IT); the former employs user perceptions as a proxy of technology (Orlikowski and Iacono, 2001), whereas the latter focuses on the technology artifact by treating the technology as a tool (Orlikowski and Iacono, 2001). In this study, we combine these two approaches to investigate the influences of product attributes and user perceptions on users’ software product preferences. Product attributes are directly controlled by the vendor and user perceptions depict individuals’ opinions. Previous research has suggested that a person’s behavior reflects how he/she perceives the important attributes of a technology (Moore and Benbasat, 1991). In this light, both product attributes and user perceptions are critical and can affect consumer choices significantly. That is, analysis of users’ software product choices should consider important product attributes and user perceptions simultaneously (Ashok et al., 2002; Luo et al., 2008). Toward that end, we attempt to address the following question:

Can we better explain consumers’ software preferences by using choice-based conjoint analysis that considers both product attributes and consumer perceptions, rather than one or the other exclusively?

This study contributes to the literature by reconceptualizing users’ technology choices with combined use of different and perhaps complementary ways of theorizing user preference that is critical to information systems (IS) research. By integrating user perceptions and objective product attributes in predicting users’ behaviors regarding software products (such as preference, choice, intention), we can provide fuller conceptualization of technology design and advance our understanding of the impacts of essential design factors individually and jointly, thereby making theoretical contributions to IS research in general and technology adoption/acceptance in particular. The proposed approach offers an interdisciplinary conceptualization and theorization and produces empirical evidence supporting such conceptualization. We demonstrate how product attributes and user perceptions could jointly determine consumers’ software choices. Furthermore, by examining the causal relationships between product attributes and perceptions, we provide valuable insights regarding the underlying process of how consumers manage the information of product attributes to make decisions. We also develop a generalizable approach to incorporate user perceptions into an optimal new product design process. For practitioners, this model can help vendors to make informed decisions on designing mobile apps. Including product price in model estimation together with other attributes can also provide insights on how users trade-off product attributes with price (Wittink and Cattin, 1989), and thus facilitate vendors’ pricing and packaging/versioning strategies.

Literature Review

This study is related to several streams of research, including consumers’ selections of software products, mobile application design, technology and product adoption, and conjoint analysis. We review each
briefly to highlight our motivation.

**Software Product Selection**

Research in software selection has mostly been done in organizational settings (e.g., Chau, 1995; Howcroft and Light, 2006; Lai et al., 2002; Liberatore and Pollack-Johnson, 2003). However, individual users consider factors that vary a lot from organizations; individuals’ software selection is another critical area that deserves in depth investigation and empirical examination.

Some critical factors influencing users’ software assessment have been identified. Prior research has pointed out that product functions are critical in users’ software assessment (Bevan, 1995; Calisir and Calisir, 2004; Nielsen, 1993). Price is another critical factor in consumers’ purchasing decisions. It not only affects users’ value evaluation, but also is used as a reference for the unobserved quality (Gerstner, 1985; Shiv et al., 2005). Nevertheless, the product price of computer software reflects only a relatively small portion of the total consumer expenditure. Consumers need to pay learning and conversion costs for using new computer software (Brynjolfsson and Kemerer, 1996; Cheng and Tang, 2010) as well. Thus, other factors influencing users’ total cost in using a software product should also be taken into consideration.

External control factors critical to users’ software selections have been also identified; they are factors external to the product designs, but the vendors somehow have direct or indirect control over these factors (Quaddus and Hofmeyer, 2007). For example, vendor support and user base are identified as decisive to users’ preferences (Quaddus and Hofmeyer, 2007). Vendor support can lower knowledge barriers and reduce the learning cost of using a new software product, and therefore is important in selecting software (Anderson, 1990; Chau, 1995; Lai et al., 1999; Lai et al., 2002). In addition, consumers prefer software that has a large user base and is perceived as a standard or compatible with other products (Farrell and Saloner, 1985). In this line, the success of a software product may depend in part on the user base, because of network externalities (Brynjolfsson and Kemerer, 1996; Cheng, 2011; Gallaugher and Wang, 2002).

**Mobile Application Design**

The new market of mobile apps has been developed by independent software vendors using the respective proprietary development kit and APIs. The constant development of mobile apps has drawn the attention of the research community to identify the market and technology trends for mobile apps (Holzer and Ondrus, 2011). For example, Holzer and Ondrus (2011) suggest that the variety of mobile devices increases the development costs for customization. It is therefore even more important for mobile app developers to carefully design the functionalities before starting the actual product development. Identifying the optimal design of mobile apps appears to be critical for vendors to reduce the development costs yet achieve success in the mobile app marketplace.

There are significant differences between mobile apps and computer-enabled applications (Pitt et al., 2011), and therefore it suggests the need to re-examine software product design issues for mobile apps (Adipat et al., 2011; Pitt et al., 2011). Various guidelines for interface design of mobile apps are also proposed (e.g., Eliasson et al., 2011; Lee and Benbasat, 2004), mainly focusing on the unique characteristics of mobile devices, such as screen size, and information presentation that are fundamentally different from personal computers (Adipat et al., 2011). Additionally, some studies have explored the process of mobile app acceptance from the perspective of new technology adoption (Faullant et al., 2012; Lee and Benbasat, 2004). Among the determinants of users’ mobile app acceptance, contextual factors have been recognized as critical (Alarcon, 2006; Biel et al., 2010; Charland and Leroux, 2011; Faullant et al., 2012), for mobile apps are often adopted in highly social contexts (Faullant et al., 2012) and therefore affects users’ choice decisions.

**Technology and Product Adoption**

Several models have been developed to explain adoption of technology and new products, including the theory of reasoned action (TRA, Ajzen and Fishbein, 1980), innovation diffusion theory (IDT, Roger, 1983)
and the technology acceptance model (TAM, Davis, 1989). The TAM was developed specifically for explaining and predicting user technology adoption behavior (Chau and Hu, 2001; Venkatesh, 2000). Overall, this stream of research emphasizes that a user's behavior reflects how he/she perceives the key characteristics of a technology or a new product (Moore and Benbasat, 1991). Specifically, individuals' perceptions predict attitudes toward adoption, and explain behavioral intentions and behavior (Chau and Hu, 2001; Davis, 1989; Davis et al., 1989; Taylor and Todd, 1995; Venkatesh, 2000). In this stream of research, product attributes such as brand, price, and functionality are generally avoided, and their influence on users’ adoption is assumed to be mediated by user perceptions. User perceptions can be perceived product characteristics (e.g., perceived ease of use and perceived usefulness; Davis, 1989; Davis et al., 1989) or contextual factors (e.g., subjective norm and product compatibility; Davis et al., 1989; Roger, 1983; Venkatesh et al., 2003). The TAM has been empirically tested in a wide array of user acceptance scenarios, including e-mail (e.g., Gefen and Straub, 1997), telemedicine (Hu et al. 1999), office automation software (e.g., Mathieson, 1991), online purchases (e.g., Koufaris, 2002), enterprise information systems (Venkatesh et al., 2003), innovative user interfaces (Agarwal and Prasad, 1999), and e-learning (Cheng, 2011). On average, this parsimonious model can explain 35–70% of the variance in intentions. Among its suggested determinants, attitude seems to be the most important predictor of intention. In turn, perceived usefulness and perceived ease of use determine attitude.

In sum, this stream of research examines consumers’ adoption behavior regarding a new technology or product. It focuses on describing the consumer’s perception of one specific product and the factors affecting consumers’ adoption decision of the given product in a generic sense. Other products introduced in the market at the same time were not taken into consideration. Thus, this research approach is rarely applied to studies of how users choose from different software products.

**Conjoint Analysis**

Conjoint analysis has been widely employed to model preferences and choices among multi-attribute products or services for over forty years (Green and Rao, 1971; Green and Srinivasan, 1990; Meyer and Sathi, 1985; Wittink and Cattin, 1989). It is based on the premise that the preference or utility for any product (or service) is equal to the sum of the part worth utilities of its attribute levels. Rather than directly ask respondents to evaluate these part worth utilities, conjoint analysis asks respondents to evaluate a number of potential product profiles whose attribute levels vary. The strength of the conjoint approach is that it combines the control of a laboratory experiment with the external validity of a survey (Tiwana and Bush, 2007).

For conjoint studies, either a rating-based (RB) design, or a choice-based (CB) design can be employed. In a RB conjoint study, respondents rate their preferences for different product profiles, and the attribute part-worths are estimated with regression. In a CB conjoint study, respondents make choices from sets of product profiles and the part-worths are estimated with logit or probit models (Karniouchina et al., 2009; Louviere and Woodworth, 1983). CB conjoint studies have been much more popular than RB since the mid-1990s primarily because the similarity between choices and actual market behavior leads to greater external validity (Elrod et al., 1992; Louviere and Woodworth, 1983) and CB conjoint models allow for market expansion and contraction as the choice alternatives are more or less attractive (Karniouchina et al. 2009).

The complexity typical of software products implies the need to manage a large number of attributes simultaneously. Hence it is appropriate to use conjoint analysis techniques (Marzocchi et al., 2003). Nevertheless, conjoint analysis has not yet been widely applied in the software product design area.

**Gap Analysis and Motivation**

The conceptualization of the IT artifacts in the information system research can be distinguished into several categories: the tool view, the proxy view, the ensemble view, the computational view, and the normal view (Orlikowski and Iacono, 2001). Among these conceptualizations, the tool and computational views focus on the technology itself. In the tool view, technology is treated as equipment. Similarly, the computational view focuses on capabilities and computational power of the technology (Orlikowski and Iacono, 2001). On the other hand, the proxy and ensemble views emphasize the human elements in
utilizing a technology. The proxy view concentrates on how a technology is viewed by individual users. The ensemble view focuses on the interactions between people and technology. Our literature review shows that research in technology adoption or software product choices also conceptualizes the technology or the software product along the lines of these views.

Most prior studies in technology and product adoption take the proxy view of technology, and some adopt the ensemble view. These studies either overlooked the probable direct effects of the technology on users’ behavior and relied on the proxies (i.e., user perceptions and diffusions among users), or omitted the influences of objective product attributes on user-perceived characteristics and treat the technology as black boxes. Specifically, they focus mainly on factors influencing perceptions and attitudes, and assume that perceptions fully mediate the impact of external stimuli on adoption. However, the assumed mediating role of user perceptions needs further validation. For example, some product attributes, such as price, can influence users’ choice directly. In addition, how various product attributes affect user perceptions remains unclear, and deserves research attention to assist product design decisions. The direct influences of product attributes on users’ choice and users’ perception should be further investigated.

On the other hand, the conjoint-oriented product design literature is congruent with the tool or computational view of the technology that focus on the IT artifacts only. It has focused primarily on a search for the attribute levels that make up optimal product profiles. Contextual factors and user perceptions are generally ignored. Nevertheless, consumer preferences are only partially captured by the direct effects of product attributes (Srinivasan et al., 1997; Tybout and Hauser, 1981). The influence of product attributes on user perceptions is also not taken into account. Since a software product is more than the IT artifact itself, the interactions between users and the product need to be taken into consideration. In order to more precisely model consumers’ product choices, there is a need to incorporate user perceived characteristics in product design (Luo et al., 2008).

While these conceptualizations of technology have provided foundations for the IS research, they however overlook some critical aspects of technology. As noted by Orlikowski and Iacono (2001) that “IT artifacts are either absent, black-boxed, abstracted from social life, or reduced to surrogate measures” (p. 130) in the majority of the IS literature, and they suggested the need to reconceptualize the IT artifact.

The effects of price on consumers’ product evaluations and purchasing are also essential and deserve continued research attention. Prior studies concerning software product price have not incorporated other product attributes to model the relative importance of product price in users’ evaluation. Additionally, vendor support and network externalities are critical for software adoption (Duan et al., 2009; Lucas et al., 1988; Tellis et al., 2009); however, they have not yet been included in product design evaluation.

In order to address these research gaps, this study proposes a model that incorporates product attributes, external control factors, user perceived characteristics, and contextual factors to estimate their joint effects on users’ choices. Additionally, the model captures the influence of product attributes on user perceived characteristics. Finally, we compare the proposed model with two alternative models that include either the latent constructs of user perceptions or product attributes, but not both. By comparing these models, we provide insights regarding a relatively effective way to model users’ preferential choices.

A prior study by Luo et al., (2008) has incorporated the user perceived product characteristics into the RB conjoint study, and show that the in-sample fit and predictive power are improved. Specifically, the in-sample fit examined by root mean square deviation (RMSD) is improved by 0.02 – 0.17; the predictive power represented by mean absolute error (MAE) is decreased by 0.016 – 0.057. However, this approach has not yet been attempted with a CB study. There is a need to incorporate user perceptions in the CB conjoint studies for several reasons. First, considering the different estimation methods, a newly proposed conceptual model needs to be operationalized and validated using both RB and CB study designs (Luo et al., 2008). Second, CB conjoint study has become the most popular type of conjoint study (Halme, and Kallio, 2011), given the benefits of the CB design, and the availability of software tools that facilitates the CB conjoint study design (e.g., Sawtooth Software). By incorporating user perceptions in CB conjoint studies, we can empirically develop the methods to estimate the effects of product attributes on user perceptions in CB studies, and suggest a generalizable approach to incorporate user perceptions for CB conjoint studies.

In addition, the perceptual measures in Luo et al.’s (2008) study (i.e., perceived power, perceived comfort,
and perceived effectiveness) are specific to the products used (i.e., a power tool and a toothbrush) and therefore may not be applicable to other product categories. On the other hand, TAM and other extended models have provided a solid theoretical foundation recognizing important perceptual factors in users’ software product evaluation. Incorporating perceptual factors based on TAM and the extended models in conjoint analysis can provide a more comprehensive and generalizable foundation for future research in software product selection.

**Theoretical Foundation and Framework**

In order to address the research questions, we develop a framework built upon existing IT conceptualizations (Orlikowski and Iacono, 2001), individuals’ information processing strategies (Jacoby, 1976; Kassarjian, 1982) and the personal construct theory (Kelly, 1970). Our proposed reconceptualization of technology is viewing IT as a combination of the vendor-controlled product attributes, external factors, user-specific perceptions, and contextual factors. As shown in Figure 1, the framework depicts the process associated with individual users’ formation of software preference.

![Figure 1. Research Framework](image)

According to the tool and computational views of IT, a software product is the composition of product design features (Orlikowski and Iacono, 2001). In this view, the software vendors have the control over what the IT is, and how the product is presented to the users. This view is also congruent with the attribute-based information processing strategy (Jacoby, 1976; Kassarjian, 1982). In the decision process of choosing a product, consumers can readily compare all products on all attributes to make choice decisions (Mantel and Kardes, 1999). For example, in the context of choosing a software product, a consumer would change his/her preference for a product because of the presence or absence of a specific functionality due to his/her needs. In sum, the tool and computational view of technology concentrates on vendor-side factors.

On the other hand, the proxy view of IT suggests the concept of IT is determined by how it is perceived by users (Orlikowski and Iacono, 2001). Using user perceptions as the proxy of a technology advocates the attitude-based information processing strategy in decision making (Jacoby, 1976; Kassarjian, 1982). It involves the use of perceptions, general attitude, past experience, impression or heuristics (Mantel and Kardes, 1999). The decision is arrived at by selecting the alternative that has been given the most favorable overall assessment (Sanbonmatsu and Fazio, 1990). This proxy view assumes that all product...
design features are fully mediated by user perceptions, and therefore is user-centric.

Nevertheless, neither the IT artifact nor the user perceptions are irrelevant. According to personal construct theory (Kelly, 1970), individuals develop internal models of reality in order to understand and explain the world around them; they develop these “constructs” based on observation. It is proposed that attributes are used as external cues to form perceptions before the preference judgment is made (Mantel and Kardes, 1999; McFadden, 1986). For example, brand names, prices and other product attributes often serve as external, heuristic cues that lead to consumers’ positive or negative perceptions. These perceptions then affect consumers’ product preferences (Maheswaran et al., 1992).

Furthermore, the ensemble view of IT suggests that technical artifacts need to be applied to some socio-economic activities. Additional resources (e.g., training and support services) and the context of applying the technology are essential to form the full “package” of technology (Kling and Schcchi, 1982; Orlikowski and Iacono, 2001). This view focuses on how new technologies come to be used (Kling and Schcchi, 1982). According to the economic choice theory approach, individuals’ decision process involves external factors, either product related or context related (McFadden, 1986). In this view, the supportive resources vendors provide (i.e., the external control factors), and the user-specific contextual factors are part of the IT conceptualization. Factors external to the products also have direct effects on users’ product preferences (Quaddus and Hofmeyer, 2007; Venkatesh et al., 2003). These factors can be fixed across individuals (i.e., vendor-controlled factors) or vary across users (i.e., user-specific factors) (McFadden, 1986). These factors do not affect product design, nor users’ perceived product characteristics.

**Research Model**

We derive a research model based on the conceptual framework and identify factors in different dimensions affecting individuals’ software product selection. These factors can be categorized as product attributes (i.e., functionality and price), external control factors (i.e., vendor support and user base) and perceived product characteristics (i.e., perceived usefulness and perceived ease of use), and contextual factors (i.e., subjective norm and compatibility). The research model is depicted in Figure 2.
In this study, software preferential choice refers to a person’s relative tendency of choosing a product comprised of a distinct combination of attributes, which differ from those of other products (Park et al., 1981). In the context of consumers’ product choices, the decision plan (i.e., the indicated preference) conveys an individual’s intention about product choice (Park et al., 1981). In this study of choice-based conjoint analysis, an individual’s preferential choice is the probability with which he/she chooses one particular alternative out of a choice set.

Product attributes are features that can be controlled and manipulated by vendors, including a set of functionalities and price. The presence or absence of a certain product function would affect users' value evaluation of the software product, based on ones' needs. Price would determine users' selection decision by influencing their judgment of whether it would be a fair transaction (Homburg et al., 2005). External control factors include the level of vendor support and the user base. A high level of vendor support can reduce users' time and effort spent to get familiarized with the software product. Although it is not a feature intrinsic to the software product, it is viewed as a part of the product package, and is taken into consideration in users' product assessment (Kekre et al., 1995). The size of user base represents the effect of network externality. Users are suspected to prefer products with a greater installed base and expect the benefit of market stability (Katz and Shapiro, 1992) and supportive content, books, manuals, and add-on products (Gallaugher and Wang, 2002).

Drawn from the literature on technology adoption (e.g., Davis, 1989; Venkatesh et al., 2003), we include perceived usefulness and perceived ease of use as the two fundamental perceived product characteristics. Perceived usefulness is the degree to which a person believes that using a specific technology would enhance performance (Davis, 1989; Venkatesh et al., 2003). Perceived ease of use, is the extent to which a person believes that using a technology would be free of effort (Davis, 1989; Venkatesh et al., 2003). The two constructs have been also tested and generalized across different contexts, and the results of these studies have converged conclusions on the effects of perceived usefulness and perceived ease of use on adoption behavior. In our case, perceived usefulness and perceived ease of use are postulated to be influenced by product functionalities only. While user perceptions refer to a user’s perceived product characteristics, external control factors normally have limited influences on the user’s perceptions. Therefore, we manipulated the product attributes and then measured the resulting perceptions. In this study, the attitude-formation perceptions are treated as latent constructs, with user ratings of the perceptions as indicator variables. As Luo et al., (2008) suggest, modeling the perceived characteristics as latent constructs (1) avoids the direct use of consumer perception ratings in the utility function, which may provide misleading results given the presence of the measurement errors (Ashok et al., 2002), and (2) allows for differences in precision of ratings among individuals.

Contextual factors, such as subjective norm (Ajzen and Fishbein, 1980) and compatibility (Roger, 1983), also shape users’ preferences. Subjective norm captures users’ perception of normative pressure; it is implied that individuals’ behavior is influenced by the way in which they believe others will view them as a result of having used the technology. Compatibility represents the perceived constraints in shaping behavioral intention and behavior (Ajzen, 1991). In our context, compatibility mainly relates to the hardware constraints of using a mobile app. The influences of subjective norm and compatibility are also widely validated and are recognized as direct determinants of behavior intention of adoption, (Venkatesh et al., 2003).

With conjoint analysis, a participant indicates his or her preferences in choice tasks comprised of profiles defined by different levels of attributes. Central to the design of a conjoint study, is the consideration of various factors that could influence an individual’s choice significantly, regardless whether the levels of an attribute can be manipulated by the vendor directly. For example, brand strength usually cannot be manipulated by the vendor, at least in a short period of time, though it could impact the premium customers are willing to pay. When using conjoint analysis to study housing choices by families, we may consider the quality of public schools, crime rate, and access to shops and public transportation to be important factors, though they are not directly controlled by housing providers. In most cases, such factors are essential and therefore should be considered when designing the respective conjoint studies. In our context, subjective norm and compatibility are contextual factors to users, which are not directly impacted by the product attributes. When subjective norm and compatibility are not manipulated in the conjoint design, they will remain constant across different profiles in each choice task presented to the participant; consequently, we cannot estimate their impacts on user preferences. In order to estimate the
effects of subjective norm and compatibility that are defined at multiple levels, we thus manipulated the contextual factors in each profile, rather than measuring them directly. In addition, subjective norm and compatibility are independent from user base and vendor support level, according to the definition we employ in our study. Thus, we did not consider the relationships between external control factors and contextual factors in our model.

**Research Design**

In this section, the modeling approach is detailed, together with the development of conjoint study design, and the study procedures.

**Model Development**

The part-worth utilities for product attributes and user perceptions are estimated by a hierarchical Bayesian (HB) structural equation model. Previous research finds strong support that individual-level HB models offer better fits and validation than comparable latent segment models (Moore, 2004). In addition, HB methods allow more accurate estimates of individual-level parameters with fewer observations (Karniouchina et al., 2009). In the HB framework, the posterior distribution of the individual part worth estimates is a weighted average of the likelihood function, estimated from that person’s responses and the prior distribution, which is the average of the sample. Because we are able to leverage the information for all the other respondents, we could obtain a weighted average of the likelihood function accomplish with fewer observations from an individual.

We estimate the following models: Model I is the proposed model, Model II uses only the product attributes to predict the consumers' choices (i.e., a traditional conjoint model), and in Model III, only the latent constructs of user perceptions are used as explanatory variables.

Let \( n = 1, ..., N \) represent the individuals, and let \( i = 1, \ldots, I \) index the product. Let \( v_{ni} \) denote the \((K \times 1)\) vector of observed ratings for user perceptions of the \( i \)th product profile; i.e., \( v_{ni} \) is the observed indicator variables. \( z_{ni} \) is the \((J \times 1)\) vector of latent constructs representing individual \( n \)'s perceptions of the \( i \)th product profile. The relationship between the observed indicator variables \( v_{ni} \) and the latent constructs \( z_{ni} \) is captured by the following factor analytic model (Rowe, 2003):

\[
v_{ni} = \Lambda_n z_{ni} + \varepsilon_{ni} \tag{1}
\]

The \((K \times J)\) matrix \( \Lambda_n \) contains the factor loadings that map the indicator variables onto the latent constructs. The term \( \varepsilon_{ni} \sim MVN(0, \Theta_n) \) represents the vector of measurement errors. It is assumed that the factor-loading matrices are invariant across individuals (i.e., \( \Lambda_n = \Lambda \), for \( n = 1, 2, ..., N \)), to make the factor scores comparable across individuals and to preserve the interpretability of the constructs (Ansari et al., 2000; Luo et al., 2008). The \((K \times K)\) matrix \( \Theta_n \) is diagonal, with the measurement error variances varying across individuals.

Let \( x_{njl} \) denote the \((M \times 1)\) vector containing the product attributes describing the \( jl \)th profile in the \( l \)th choice set seen by person \( n \). Then the structural equation relating the product attributes to the user perceptions for each individual is as follows:

\[
z_{njl} = \delta_n + B_n x_{njl} + \mu_{njl} \tag{2}
\]

where \( \delta_n \) denotes the \((J \times 1)\) vector of individual differences. \( B_n \) is a \((J \times M)\) coefficient matrix denoting the effects of \( x_{njl} \) on \( z_{njl} \), and the \( \mu_{njl} \sim MVN(0, \Lambda_n) \) represents the disturbance terms; we allow the variance-covariance matrix \( \Lambda_n \) to vary across individuals. In the calibration sample, the posterior distribution of the factor scores \( z_{njl} \) is estimated on the basis of the priors and information from two data sources: the measurement equation (i.e., equation (1)) and the structural equation (i.e., equation (2)).
Therefore the full conditional distribution of $z_{njl}$ is $\text{MVN}(\omega_{z_{njl}}, \Delta_{z_{njl}})$, where

$$\omega_{z_{njl}} = \Delta_n^{-1}(\delta_n + B_n x_{njl}) + \Lambda^\prime \Theta_n^{-1} v_{nl}, \quad \Delta_{z_{njl}} = \Delta_n^{-1} + \Lambda^\prime \Theta_n^{-1} \Lambda.$$ 

Let $P_{njl}$ be the probability that person $n$ chooses alternative $j$ out of the $l$th choice set whose elements are indexed by $m$, we then have the following equation for the proposed model (Model I):

$$P_{njl} = \frac{e^{\hat{\Lambda}_n^\prime x_{njl} + \hat{\Gamma}_n^\prime z_{njl}}}{\sum_m e^{\hat{\Lambda}_n^\prime x_{nm} + \hat{\Gamma}_n^\prime z_{nm}}}$$ (3)

$x_{njl}$ is a $(P \times 1)$ vector containing the description of product attributes for the $j$th profile in the $l$th choice set seen by individual $n$, and $\hat{\Lambda}_n$ is a $(P \times 1)$ vector of importance weights. $z_{nml}$ is a $(Q \times 1)$ vector representing individual $n$'s perceptions the $m$th profile in the $l$th choice set, and $\hat{\Gamma}_n$ is a $(Q \times 1)$ vector of importance weights.

Model II uses only product attributes, and the equation as follows:

$$P_{njl} = \frac{e^{\hat{\Lambda}_n^\prime x_{njl}}}{\sum_m e^{\hat{\Lambda}_n^\prime x_{nm}}}$$ (4)

Model III uses only the users' latent perceptions as predictors, resulting in the following equation for user choices:

$$P_{njl} = \frac{e^{\hat{\Gamma}_n^\prime z_{njl}}}{\sum_m e^{\hat{\Gamma}_n^\prime z_{nm}}}$$ (5)

Individual choice predictions are based on a maximum utility model. Choice shares were predicted by summing individual choice probabilities over the sample.

**Development of the Conjoint Product Profiles**

This study focuses on mobile apps. In addition to their importance in today's software market, they are under researched, and few categories are dominated by one particular app. A note-taking app, which is a tool for increasing productivity, is chosen in this study. This type of applications is used for taking notes, prioritizing to-dos, and integrating with calendars. It is among the most popular types of mobile apps that users are willing to pay for\(^1\), and represents how mobile apps are used in daily life. In this study, the product attributes are selected based on: (1) their importance to the end user, and (2) their relevance to the user perceived characteristics (Luo et al., 2008). For example, neither customized background setting nor the font and color settings are included because they do not influence the perceived ease of use or perceived usefulness of the app. The factors included in the conjoint design and their levels are as shown in Table 1. Most mobile apps are priced at $0.99 (about 85,000 apps) and only around 850 apps are priced at $9.99\(^2\). Thus we used $0.99 and $9.99 to represent the widely accepted price versus a less popular price.

\(^1\) According to Nielsen research (2011), productivity applications are downloaded by 21% of the past-30-day downloaders.

Table 1: Factors (and levels within factors) used in this study

<table>
<thead>
<tr>
<th>Category</th>
<th>Attributes</th>
<th>Levels</th>
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<tbody>
<tr>
<td>Product Attributes</td>
<td>Function: Attachment</td>
<td>Present</td>
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<tr>
<td></td>
<td>Function: Full-text search</td>
<td>Present</td>
</tr>
<tr>
<td></td>
<td>Function: Tags and dates</td>
<td>Present</td>
</tr>
<tr>
<td></td>
<td>Function: Synchronization</td>
<td>Present</td>
</tr>
<tr>
<td></td>
<td>Price</td>
<td>$9.99</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$0.99</td>
</tr>
<tr>
<td>External Control Factors</td>
<td>User base</td>
<td>&gt;=60%</td>
</tr>
<tr>
<td></td>
<td>Vendor Support</td>
<td>High</td>
</tr>
<tr>
<td>Contextual Factors</td>
<td>Subjective Norm</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>Compatibility</td>
<td>High</td>
</tr>
</tbody>
</table>

Respondents were presented with choice tasks that contain randomized profiles generated by Sawtooth Software’s SSI Web experimental design module with the complete enumeration strategy. The complete enumeration strategy considers all possible profiles and chooses the one that produces the most nearly orthogonal design for each respondent. The product profiles within each task are also kept as different as possible to ensure minimal overlap (Johnson and Orme, 1996). Accordingly, a different version of the survey was generated for each participant.

**Study Design and Procedure**

The survey was conducted via a Web-based interface. A mixed sample of undergraduate and graduate students from a U.S. university was used in this study due to their familiarity of mobile apps. Participants were first asked to provide background information (i.e., gender, age, major, and years in college). They were then asked to imagine that they were searching for a note-taking app. Each function was explained with screenshots of the focal app, and other factors are described verbally. They received the same description of the factors. Then they received eight choice sets, which included three app designs as well as the option of choosing none of them. For each choice task, the provided functions were shown to the participants, as well as the price, vendor support level and the user base information. Descriptions of different selection scenarios (different levels of subjective norm and compatibility) were also provided. At this stage, we did not ask for the participants’ perceptions of the products, because prompting inferences may significantly alter consumers’ preferences (Huber and McCann, 1982).

In the next stage, we collected the participants’ perceptions for four product profiles. The same set of four product profiles was shown to all the participants and they were asked questions about the perceived usefulness and perceived ease of use for each product profile. Only product functionalities are manipulated in this stage, because in our model set up, users’ perceived usefulness and perceived ease of use are affected by only product functionalities. Perceived usefulness and perceived ease of use were measured using established scales by Venkatesh et al., (2003).

**Data Analyses and Results**

The data were collected from 105 participants from the targeted sample pool. Among the participants, 65.1% are male and 34.9% are female; the average age is 25.16, and the average number of years in college is 3.81. Among the eight choice tasks each participant completed, data from six randomized choice tasks were used for calibration, and the data of other two fixed choice tasks were used as holdout choice tasks.

3 All of the participants used mobile apps every day at least 3 times, and owned their own smartphones.
4 Choice experiments typically employ an alternative of “choose none”, “stay with current product”, or, “keep on shopping” so the respondents are not forced to choose any of the alternatives if they are insufficiently attractive. This allows one to model changes in the size of the overall market (Karniouchina et al., 2009).
sets for evaluation.

Table 2 summarizes the in-sample fit. To assess relative posterior fit, we compare the posterior probability of the data conditional on each model, or the log marginal density (Newton and Raftery, 1994). The log marginal density is approximated by the harmonic mean of the likelihoods of the data from the posterior distribution across MCMC sampling iterations. Larger values (i.e., less negative values) of the log marginal density indicate a preferred model. Note also that the log marginal density includes an automatic penalty for a model with more parameters (Rossi et al., 2005). By comparing the log marginal density of the models, it shows that the proposed model (i.e., Model I) fits the data better (log marginal density = -269.562) than the other two benchmarking models (log marginal density = -310.305 and -790.125 respectively).

<table>
<thead>
<tr>
<th>Table 2. In-sample Fit</th>
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<tr>
<td></td>
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<tr>
<td>Model I</td>
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<tr>
<td>Log Marginal Density</td>
</tr>
<tr>
<td>-269.562</td>
</tr>
</tbody>
</table>

Table 3 shows the holdout choice set validation results. Each individual’s choices were predicted using the estimated utility functions. We then compare the percent of the time that the model correctly predicted each individual’s choices. The validation is based on two holdout choice sets of three app designs and the option of choosing none. Individual choices are simulated using a maximum utility choice rule. The results of individual-level hit rates show that the prediction hit rate of the proposed model (0.657) is higher than the benchmark models (0.629 and 0.238). The prediction validation is also done at the aggregate-level, by computing the mean absolute deviation (MAD) between the predicted and actual choice shares, over all alternatives and choice sets. The results show that the proposed model validates better than the other two models.

<table>
<thead>
<tr>
<th>Table 3. Prediction Result of Holdout Choice sets</th>
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<tbody>
<tr>
<td>Model I</td>
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<tr>
<td>Holdout Hit Rate</td>
</tr>
<tr>
<td>Mean Absolute Deviation</td>
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</table>

Table 4 shows the parameter estimates for Model I. The first two columns give the posterior mean relationships between the objective product characteristics and the perceptions. The final column gives the importance weights in the logit model. The functions of editing tags and synchronization have the most prominent effect on users’ perceived usefulness, followed by the function of search. All functions are positively related to perceived usefulness. As for the effects of product functions on perceived ease of use, the functions of editing tags and synchronization have positive effect, while attachment and search are negatively related to perceived ease of use. Based on this result, the functions of editing tags and synchronization can induce positive user perceptions.

As for purchase intention across individuals, the two most important variables are compatibility and price and their magnitudes are comparable (i.e., 6.529 and -6.285). The two factors dominant users’ purchase intention. The mobile app vendors therefore should cautiously consider them in making their marketing strategies. For example, the vendors can develop an application that can be run on various mobile platforms, or use the standard development kit to ensure its compatibility. It also justifies why most of the current mobile apps on the market are priced at $0.99. On the other hand, the effect of perceived ease of use on purchase intention is relatively small. It may due to the simplicity of mobile app user interface, and users do not consider the ease of use would be a major issue in using a new mobile app. The learning cost of mobile apps does not seem to be an issue for most users. In addition, users weight the vendor support level higher than the ease of use of the app itself, it implies that good vendor support can offset the

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5 It is possible that Model III fits much worse than the other two because the perceptions do not capture either price or compatibility, which will be shown to be very important variables.
negative effect of a not-so-easy-to-use app.

<table>
<thead>
<tr>
<th>Table 4. Summary of Parameter Estimates by the Proposed Model</th>
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<tbody>
<tr>
<td>Perceived Usefulness</td>
</tr>
<tr>
<td>-----------------------</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Function: Attachment</td>
</tr>
<tr>
<td>Function: Search</td>
</tr>
<tr>
<td>Function: Tags</td>
</tr>
<tr>
<td>Function: Sync</td>
</tr>
<tr>
<td>User base</td>
</tr>
<tr>
<td>Vendor support level</td>
</tr>
<tr>
<td>Price</td>
</tr>
<tr>
<td>Subjective norm</td>
</tr>
<tr>
<td>Compatibility</td>
</tr>
<tr>
<td>Perceived usefulness</td>
</tr>
<tr>
<td>Perceived ease of use</td>
</tr>
</tbody>
</table>

Note: Population posterior standard deviations appear in parentheses.

In addition, the total effect of the functions on purchase intention can be calculated as following: attachment 3.334, search 3.962, tags 0.935, and sync 2.479. That is, the functions of attachment and search are also relatively important in affecting users’ choice decisions, and editing tags is the least influential function. For a note-taking app, the search function can help the users quickly find the information they need and therefore they can greatly improve users’ purchase intention. The attachment function allows users to link a note to related files, and may help users to better organize related information. Alternatively, assigning tags to notes may not appeal greatly to users; having this function would be a plus to the mobile app, but does not add much value to the app. With such information, the app vendor can make a better decision on whether they should include the function or not.

In addition to the aggregate level results shown in Table 4, the app vendor can also segment the population using clustering analysis based on the individual-level coefficients. Since users may have heterogeneous preferences, each of these coefficients is given an independent normal distribution with mean and standard deviation that are estimated. The coefficients of variables can take either sign for users having opposite preferences. The coefficients for the function of attachment, search, tags, price and compatibility have the same sign for most users, with only their magnitudes differing. However, the coefficients for other factors vary greatly across users; for example, the standard deviations of the coefficient for perceived usefulness and perceived ease of use are high relative to their means, indicating that those coefficients vary significantly in the population. Observation of the standard deviations of the coefficients indicates that there is considerable variation in the individual preferences that is hidden by data aggregation.

The means and standard deviation of these coefficients further provide information on the share of the
population that places a positive value on a factor and the share that places a negative value. For example, the distribution of the coefficient for the function of editing tags obtains an estimated mean of 0.493 and estimated standard deviation of 0.932, such that about 63% of the distribution is above zero and 37% below. The coefficients for perceived usefulness (mean = 0.109; standard deviation = 0.585) show while 54% of the users prefer mobile apps with high perceived usefulness, 46% of the users have different preferences. One of the possible explanations is that some users would prefer mobile apps with only minimum essential function and less perceived usefulness, given the hardware limitations of a mobile device. The coefficients for perceived ease of use (mean = 0.081; standard deviation = 0.433) show that 53% of the users prefer mobile apps with high perceived ease of use. It is possible that the users prefer mobile apps with more functions even though they are not as easy to use.

**Discussion**

These findings offer several implications for research. First, our proposed conceptualization of IT can better capture how users evaluate and make choices among competing software products. According to the study results, the concept of IT goes beyond the artifact itself or the users’ personal perceptions. IT artifacts are made up of components that interconnect with each other. The tool view or proxy view of the IT can only represent part of the whole picture, and limit our understanding of the impact of IT. Second, the study results show that users take a dual information processing strategy in choosing software products. Prior research has identified the distinction of the two processing strategies, and the decision context in which each strategy would be used (e.g., Mantel and Kardes, and, 1999; Sanbonmatsu and Fazio, 1990). The study further suggests a new context that the two strategies are not used solely in the decision process, in light of the importance of personal construct theory. For example, attribute-based decisions are made when users attend to details and are motivated to form accurate judgments, and the attitude-based judgments are also made on the basis of personal idiosyncrasies, which represent the way individuals make sense of the world.

Third, the importance of user perceptions cannot be overlooked, even though the relative importance of product attributes is much greater than user perceptions in the context of this study. The results exhibit that users’ perceptions are not independent from the product attributes. The inclusion of user perceptions can help us more accurately capture the total effect of product attributes, and provide insights into how product designs can alter user perceptions. For example, a tool for custom reporting of a software product may induce positive perceived usefulness but negative perceived ease of use, due to the complexity of function. In this context, a model without both product attributes and user perceptions may not be able to provide insights on how to improve the product design to promote user preference of the product.

For practitioners in the product design area, we contribute to current practices by developing an alternative method for understanding and analyzing user preferences. We propose an alternative and arguably a more holistic approach to explain user preferences of different software designs, which considers both product attributes and user perceptions. When using our approach to analyze a particular software product, investigators should identify the important functionalities specific to the product and consider the essential characteristics of target user groups. That is, the underlying conjoint analysis needs to tailor to the specific software product and target users. Supported by our approach, software developers and vendors could effectively model product functionalities and user characteristics to make appropriate design decisions.

**Conclusion**

In this study, we propose an integrated reconceptualization of IT that incorporates the tool, proxy and ensemble views of IT. We also develop a choice-based conjoint model to incorporate the product attributes, external control factors, user perceptions, and contextual factors in predicting users’ software choices. The influences of the product attributes on users’ perceived product characteristics are also examined. Our study results show that the proposed model can better predict users’ software choices than models using product attributes or user perceptions exclusively.

This study contributes to the IS literature by proposing a new conceptualization of IT. Compared to existing ways of theorizing IT, our approach can provide a better understanding of how various IT
components jointly contribute to consumers’ software selection decisions. We also provide evidence that this conceptualization of IT can be operationalized and used in empirical investigations to better estimate the influence of different technologies. While prior IS research mainly focuses on users’ perceptions in explaining user behavior, the results of this study suggest the importance of the direct and indirect effects of product attributes. In addition, this study contributes to the software product design literature by showing how the external stimuli affect users’ perceptions, and then lead to users’ software choice decisions. While user perceptions are generally assumed to mediate the effects of product attributes, we provide empirical evidence of the mediating effect of user perceptions on users’ software selections, and further offer insights into how the product design would affect user perceptions.

This study contributes to the literature by incorporating both product attributes and user perceptions in a choice-based conjoint study. While prior literature has suggested such an approach in rating-based conjoint designs, choice-based designs provide greater ability to model whether a customer makes a purchase from a product class or not, and presents the choices in a more realistic way to respondents. While choice-based design is now the most popular and widely adopted conjoint design, the study suggests a new approach of incorporating user perceptions to this research stream.

In addition, the approach we propose in this study includes two different types of user perceptions: perceptions independent from product attributes (e.g., contextual factors) and perceptions affected by product attributes (e.g., perceived usefulness and perceived ease of use). Although we controlled the contextual factors as part of the product profile evaluated by users, our approach can be applied to studies that collect users’ perceptions of the context and other factors independent from the product attributes. This approach is therefore flexible in applying to various conjoint research designs.

However, this study also has several limitations that should be considered when interpreting the results. First, these studies are based on a sample of volunteer participants. Although the participants can reasonably represent the user group of mobile apps, we cannot rule out potential self-selection biases completely. Therefore, the findings should be generalized only cautiously. Second, the study design limits the ability to address potential interaction effects among the product attributes, due to the concerns of the number of choice tasks of each participant. The main purpose of the study is to compare a model incorporating both product attributes and user perceptions, to a model with product attributes only and a model with user perceptions only. While examining the main-effects-only model is sufficient for that empirical investigation, including interaction effects in the model may provide more information toward users’ product choice decisions. Third, perceived usefulness and perceived ease of use are used in this study to represent the perceptions affecting users’ package software choices. While prior literature has identified perceived usefulness and perceived ease of use as the most prominent perceived factors in users’ technology adoption decisions (Venkatesh et al., 2003), a broader set of user perceived product characteristics can be examined in future studies.

These limitations suggest several other important research directions. For example, researchers should examine user perceived product characteristics affecting dynamic product choices, such as look-and-feel, perceived usability, perceived observability, and perceived learnability. Similarly, other contextual factors can be also incorporated; e.g., triability. In addition, mobile apps only represent only one category of software products; further research could examine the applicability of our approach using different types of software (e.g., such as operating systems, graphic design and process, statistics, computer-aided design) or various user groups. Further study on interaction effects of product attributes and user perceptions also deserves attention.

References


