Association for Information Systems
AIS Electronic Library (AISeL)

ACIS 2010 Proceedings | Australasian (ACIS)

2010

The Utility of TAM-Perceptions: Integration of Technology Perceptions into Choice-Based Conjoint Analysis

Markus Lilienthal
Goethe-University Frankfurt, messerschmidt@wiwi.uni-frankfurt.de

Christian M. Messerschmidt
Goethe-University Frankfurt, messerschmidt@wiwi.uni-frankfurt.de

Bernd Skiera
Goethe-University Frankfurt, skiera@wiwi.uni-frankfurt.de

The Utility of TAM-Perceptions: Integration of Technology Perceptions into Choice-Based Conjoint Analysis

Markus Lilienthal
Email: lilienthal@wiwi.uni-frankfurt.de
Christian M. Messerschmidt
Email: messerschmidt@wiwi.uni-frankfurt.de
Bernd Skiera
Email: skiera@wiwi.uni-frankfurt.de
Goethe-University Frankfurt
Germany

Abstract

Recent papers claim the technology acceptance model [TAM] is exhaustively examined by researchers and, thus, additional studies of traditional style may only provide a marginal contribution. Instead of adding new constructs to the TAM to describe its dependent or independent variables better, we develop an approach to combine the well-established constructs of TAM, which measure perceptions of a new technology, and the choice-based conjoint analysis [CBC], which measures the monetary value of product attributes from a marketing perspective. In combining both methods we are able to compare the overall technology perceptions with particular attributes of product realisations with respect to their importance. We measure how TAM constructs influence the baseline utility of a new technology. We empirically apply and discuss our approach and show how the TAM can make a distinctive contribution to Information Systems and Marketing Research.

Keywords: Technology Acceptance Model, Choice-Based Conjoint Analysis, No-Choice-Option, Latent Variables, Product Innovation.

INTRODUCTION

A number of researchers in the recent years engaged themselves in analysing and enhancing the technology acceptance model [TAM] (Davis 1989), a structural equation model for measuring the adoption of new technologies. Most of the studies either assigned TAM to new technology domains which had not yet been examined with TAM, integrated new constructs to increase the explained variance in the measured adoption intention, or discussed the reduction of extensive TAMs in terms of deleting constructs in order to reduce complexity. Overall, we observe the research in TAM was primarily focused on adding and deleting constructs in the model rather than extensions beyond the model. Critical voices now raise the question whether this stream is exhausted and a new focus needs to be set (Benbasat and Barki 2007).

In Marketing and Business Economics the standard assumption is that a product will be purchased if the overall utility of the product is higher than not to purchase. The utility of the product is consumer-specific and has three constituents. First, there are latent perceptions of the technology. Second, there are clear product attributes such as brand, colour, size, certain functionalities, or technical properties. Third, the price is of very special interest for marketers. A classical TAM has limited value for marketers, because they need practically meaningful outcomes such as the percentage of consumers purchasing a particular product–and TAM does not yield this information.

Information Systems research has shown that perceptions, the first utility constituent, are extremely important for the adoption of new technologies. The latent constructs *Perceived Usefulness* [PU] and *Perceived Ease of Use* [PEOU] are identified and confirmed as fundamental perceptions in technology adoption models. They can significantly describe and predict the individual's attitude towards an innovative technology and, thus, his/her adoption intention (Straub and Burton-Jones 2007; Venkatesh and Bala 2008). These two constructs capture all relevant beliefs in new technologies and are easily transferable to almost any kind of technology (Benbasat and Barki 2007). In many studies TAM was extended by additional constructs representing technology-specific aspects or individual differences, which were implemented to either better explain the attitude and adoption intention or PU and PEOU (Bagozzi 2007; Benbasat and Barki 2007). But eventually PU and PEOU are almost always in the model's spotlight.

The product attributes and price in contrast are the utility constituents that are usually regarded in marketing research. A frequently used and very successfully applied method in marketing science to estimate preferences, the individual's utility of an entire product offer and thus, in a way, the purchase intention of an individual for a specific product offer is the survey-based choice-based conjoint analysis [CBC] (Louviere et al. 2000; Louviere and Woodworth 1983). In the last decade the CBC was increasingly deployed by practitioners in market research for consumer goods. CBC is basically a repeated-design choice experiment in which consumers are asked to choose a product out of different alternatives or none of them (no-choice-option). With a special design, the CBC is even able to transfer the estimated utility for an innovative product-offer into monetary values in terms of willingness-to-pay [WTP].

Two disadvantages of the CBC are conspicuous: (1) A CBC survey should only consider a selection of up to six product attributes. Otherwise the survey will get to extensive for the responding consumer (Green and Srinivasan 1990; Scholz et al. 2010). Restriction to the most important attributes can be very hard, especially for new products emerging from new technologies. (2) A CBC can only estimate the preferences and utilities for product attributes and provides no conclusion of the general attitude and adoption intention towards the entire technology. But these latent variables may also have a distinct impact on choice decision and, thus, the purchase intention of an individual (Ben-Akiva et al. 1999; Ben-Akiva et al. 2002; Walker and Ben-Akiva 2002). In case of a CBC-survey with selected product attributes that are not interesting or represent knock-out criteria for the consumer, it may appear that the generated product-offers in the CBC will be poorly evaluated despite a positive attitude and adoption intention towards the entire technology. Regarding the decision about the launch such an outcome can lead to significant misconceptions.

The combination of an approach measuring the general attitude towards a technology (TAM) based on latent variables and an approach focusing on preferences for specific product attributes (CBC) has the potential to solve the outlined problems of CBC, make the results of TAM more practically applicable, and introduce TAM into a research-domain where it can contribute remarkably. There are only few articles that enrich CBC with latent variables such as the technology perceptions of the TAM and none has yet analysed the impact of perception on the utility of new technologies. The aim of this article is to present an approach that combines TAM and CBC to (1) transfer the technology perceptions PU and PEOU into utility values and (2) identify whether the selection of the product attributes in the CBC-design is well-determined. We present an application showing that the importance weight of the perceptions can be even higher than those of classical product attributes.

THEORETICAL BACKGROUND

Innovations and New Product Development

Product Innovations have a long research tradition in Information Science, Marketing and Management. Definitions of the term *innovation* agree that innovations are heterogeneous. Innovations range from incremental product alterations up to new-to-the-world products. Kleinschmidt and Cooper (1991) in detail distinguish three types: highly innovative products are new to the world or at least new product lines. Low innovative products are minor modifications redesigns to achieve cost reduction and repositionings. Moderately innovative products cover the bandwidth in between. Garcia and Galatone (2002) argue that innovations can refer to a new technology or a new market or both of them and occur on micro versus macro level. Radical innovations at the top of the hierarchy such as the WWW or the steam engine are new technologies on macro level that create an entire new market. Garcia and Galatone (2002) map the degree of innovativeness onto the s-curve of technical performance as the output of research and marketing effort. Their view underlines the two faces of innovations: the more objective technological face and the more diffuse marketing face. The paper of Kleinschmidt and Cooper (1991) belongs to a stream of research that identifies the success factors of new products. The stream goes back to Myers and Marquis (1969) and the success/failure study SAPPHO (Freeman et al. 1974; Rothwell 1972). Both studies identify understanding the users' needs as the key success factor. The subsequent stream strengthened the findings (Brown and Eisenhardt 1995), and the focus has changed now on new questions, e.g. the role of strategies (Paladino 2007; Sivadas and Dwyer 2000).

Technology Acceptance Model [TAM]

The information systems research explores the consumers' attitude towards an innovation in finding out why consumers want to use a technology or not. The most accepted model to analyze the individual adoption of a technological innovation is the Technology Acceptance Model [TAM] (Davis 1989) which is based on Ajzen's Theory of Reasoned Action [TRA] (Ajzen and Fishbein 1980). TAM hypothesises that the usage of a system is directly determined by the *Behavioural Intention* [BI] to use/adopt it. Ajzen and Fishbein (2010) found a strong significant correlation of 0.75 between the BI of students to donate blood and their real behavior, which was measured one week later. This outcome underlines the strong relation between a self-reported intention and the future behavior of an individual. BI in turn is influenced by the *Attitude Towards Using a New Technology* [Attitude] and the *Perceived Usefulness* [PU] of the new technology. Attitude and PU are again influenced by the *Perceived Ease of Use* [PEOU] of the new technology. Hence, PU and PEOU are expected to be the main drivers of technology adoption in the well-established TAM. PU measures the individual's subjective assessment of the utility that the new technology is offering her/him in a specific task-related context. Whereas PU was originally deployed with respect to the individual's job performance, a number of studies show that PU can also be used in non-organizational settings (Gefen et al. 2003). PEOU explains the individual's salient beliefs that using the technology will be free of physical and mental effort (Moore and Benbasat 1991). A number of empirical studies are supporting TAM as a robust approach to explain the individual's adoption and acceptance of information technology (Lee et al. 2003; Lucas Jr et al. 2007) as well as in the domain of online services (Gefen et al. 2003; Wu and Chen 2005) and identify both PU and PEOU as main drivers of new technology adoption (Benbasat and Barki 2007; Straub and Burton-Jones 2007).

Choice-Based Conjoint Analysis [CBC]

CBC is a decompositional analysis method where, based on hypothetical choice decisions between different alternative products, conclusions about the utility and willingness-to-pay of product attributes can be made (Green and Srinivasan 1978; Louviere 1988). Generally, a product alternative in CBC, also called stimulus, is characterized by a number of attributes with predefined sets of attribute levels. The set of all alternatives which is presented to the consumer is called a *choice set*. A CBC survey contains 10 to 20 choice sets with a varying composition of product alternatives to gain sufficient data for the coefficient estimation. Thus the respondents have to decide repeatedly which of the displayed (varying) stimuli they prefer. Usually, CBC does not artificially force the consumer to decide for one stimulus in case neither of them is valuable. This is realized in adding a no-choice-option to the choice set (Brazell et al. 2006; Ding et al. 2007). The ability to resemble real shopping behaviour is often discussed as a major benefit of the CBC (Cohen 1997). The consumer does not have to evaluate explicitly each stimulus or attribute, but instead only chooses the most preferred alternative like in a real shopping environment.

CBC assumes that consumers maximize utility. Utility is a real number assigned to each option. The no-choice option also has a fixed, yet unknown utility. The higher the utility, the more valuable is the product for the consumer. Usually the utility is modelled as a linear function of the attributes plus a stochastic component:

$$\text{(1)} \qquad u_{h,i} = x_i' \cdot \beta_h + p_i \cdot \omega_h + \varepsilon_{h,i} \qquad (h \in H, i \in I),$$

where $u_{h,i}$ represents the total utility of the product i of consumer h, x_i is the vector of attribute levels of product i except the price p_i with individual coefficient ω_h, β_h is the vector of the preferences (coefficients) of consumer h and $\varepsilon_{h,i}$ represents the stochastic part of the total utility of product i of consumer h. I denotes the index set for all products and is the index set of all consumers. Based on the assumption that consumers want to maximise their total utility, they will choose the product of highest utility (Louviere et al. 2000). Because of the stochastic utility component the actual choice is probabilistic as well. Assuming the stochastic utility components are Gumbel-distributed, a Multinomial Logit Model (MNL Model) describes the choice probability $P_{h,i,a}$ of stimulus i, consumer h, and choice-set a (Louviere et al. 2000; Train 2009):

$$\text{(2a)} \qquad P_{h,i,a} = \frac{\exp(x_i \cdot \beta_h + p_i \cdot \omega_h)}{\exp(u_{h,0}) + \sum_{i' \in C_a} \exp(x_{i'} \cdot \beta_h + p_{i'} \cdot \omega_h)} \qquad (h \in H, i \in I),$$

where $u_{h,0}$ is the deterministic utility of the no-choice-option for consumer h, and the other variables as above. C_a denotes the index set all choice alternatives in choice-set a disregarding the no-choice-option ($i = 0$) and A denotes the set of all choice sets. The probability of choosing the no-choice-option is accordingly

(2b) $$P_{h,i,a} = \frac{\exp(u_{h,0})}{\exp(u_{h,0}) + \sum_{i' \in C_a} \exp(x_{i'} \cdot \beta_h + p_{i'} \cdot \omega_h)} \qquad (h \in H, i \in I).$$

The coefficients are estimated by likelihood maximization, where the likelihood is the product of the probabilities of the chosen alternatives i_a, i.e. all choices are assumed to be stochastically independent:

(3) $$L = \prod_{h \in H, a \in A} P_{h,i_a}$$

The extension Mixed Multinomial Logit (MMNL) yields consumer-individual estimates (Train 2009) which are necessary for analysing individual preferences. MMNL provides a flexible and computationally practical approach for that (McFadden and Train 2000). It is a generalisation of the basic choice model where consumers have heterogeneous preferences and thus coefficients. MMNL assumes that a predefined heterogeneity distribution with unknown parameters describes the variety of true coefficients. The choice probabilities $P_{h,i,a}$ are the respective probabilities with respect to the heterogeneity distribution. The coefficients and heterogeneity parameters are estimated by maximum simulated likelihood, because the integrals cannot be algebraically computed. The method does not yield individual coefficient estimates, but individual distributions of them instead. The expected value serves practically as an individual coefficient estimate.

Integrating Latent Variables into Choice Models

In the literature regarding discrete choice modelling it is often discussed that the decision process and the resulting choice of an individual may not only be influenced by observable variables (e.g. product attributes). Latent variables (e.g. psychological constructs like values, attitudes, motives and perceptions, which are typical for TAM) may also have a distinct impact on the utility of the choice alternatives and, thus, finally the choice decision of an individual (Ben-Akiva et al. 1999; Ben-Akiva et al. 2002; Walker and Ben-Akiva 2002). However, the combination of latent variable models and discrete choice models is a domain of scarce research (Temme et al. 2008). One of the first general conceptual models which incorporated latent variables in discrete choice models was developed by Ben-Akiva et al. (1999), but not empirically verified. Ashok et al. (2002) took on this approach and empirically compared different limited information baseline models (that integrate only the manifest variables (items) without consideration of the inherent error or no latent variables at all) with different full information models (latent variables as constructs with consideration of an error term). The full information models explicitly were exposed to have the better fit to the data. Temme et al. (2008) combined the discrete choice model with a complete structural equation model and examined travel mode choice. They also found that integrating the latent variables leads to a better fit. Their focus necessitated the modelling of complex interrelationships between latent variables and the valuation of CBC attributes. We in contrast sharply distinguish the perception of the technology in general and attributes of the product in particular, so that we neither expect nor actually observe considerable interrelation effects. Moreover, we benefit from TAM as an established behavioural theory.

METHODOLOGY

Our methodology is a two-step estimation approach, which is displayed in Figure 1. In the first step we conduct a CBC accounting for heterogeneity. As a result we receive the individual utilities of the product attributes and of the no-choice option for each respondent. In the second step we estimate the effect of the TAM constructs PU and PEOU on the utility of the individual no-choice-option such that they can be directly compared to the products' attributes. To simplify the comparison we transform the utility effects into percentages representing the importance weight of each product attribute for the product's total utility.

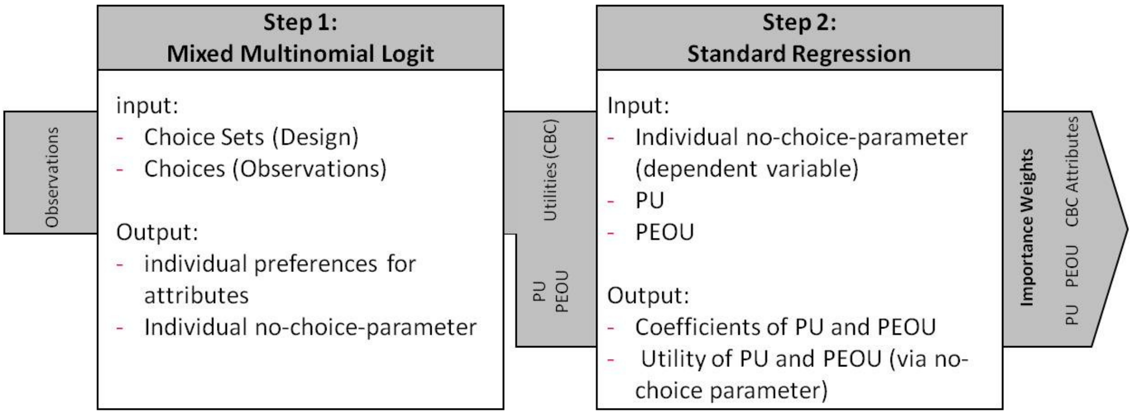

Figure 1: Methodology

As an illustration of the motivation of our approach, assume there are two different consumers. Consumer A has a highly positive attitude towards the technology. His/her willingness-to-pay is much higher and he/she will less often pick the no-choice-option. Consumer B in contrast has a negative attitude toward the technology, e.g. it does not fit into his/her way of life or the usage of the technology is too complicated. Consumer B is therefore willing to pay not as much as consumer A and he/she will more often pick the no-choice-option. Consequently, B has a higher utility of the no-choice-option. Our hypothesis is that the technology perception negatively affects the utility of the no-choice-option and thus the no-choice-option utility is the linking element between the perceptions and the product attributes. The TAM constructs PU and PEOU and their items refer to the technology in general, not to specific products. Therefore there is no reason why the constructs should have any effect on selective stimuli other than the no-choice-option. Also, we empirically find out that the constructs have no significant effect on price at all. Hence it is false that a higher utility comes along with a different related willingness-to-pay.

In detail we start with a choice experiment and subsequent Mixed Multinomial Logit estimation. We use dummy-coding for all binary or nominal attributes and operationalize the no-choice-option utility as a dummy indicator variable included in the vector x_i in formula (1). For all other stimuli (except the no-choice-option) this variable is set to 0. For the no-choice-option all entries of x_i except the no-choice-option dummy x_i are set to 0. Thus the individual no-choice-option dummy is equal to the estimated no-choice-option utility. We also code the price as dummy variable (partworth utility model) instead of a linear variable (vector model), because we observe a smaller marginal (absolute) utility of price for small prices between 20€ and 30€ in our application.

The second step is a standard regression where the construct values (average of the corresponding item values) of PU and PEOU explain the individual no-choice-option utility as dependent variable. PU and PEOU are not correlated in our application. Constructs explaining them might also be considered alternatively, but they strongly depend on the analysed technology in contrast to PU and PEOU, which are fundamental and universal in TAMs and extended models as well.

The estimates of the first and second step are all we need for computing the importance weights of both product-specific attributes and technology perceptions. The importance weights of the attributes are the differences in utility between best and worst possible attribute level, usually written as percentages. We extend this definition by defining the importance weight of perceptions (average of several Likert scale items) accordingly: the estimated coefficients of the second step yield how much a one-point increase in the value of the perception-construct decreases the no-choice-option utility, which is equal to the difference in total utility. As we used a seven-point Likert scale, the difference between best and worst perception will not exceed six points in our empirical study.

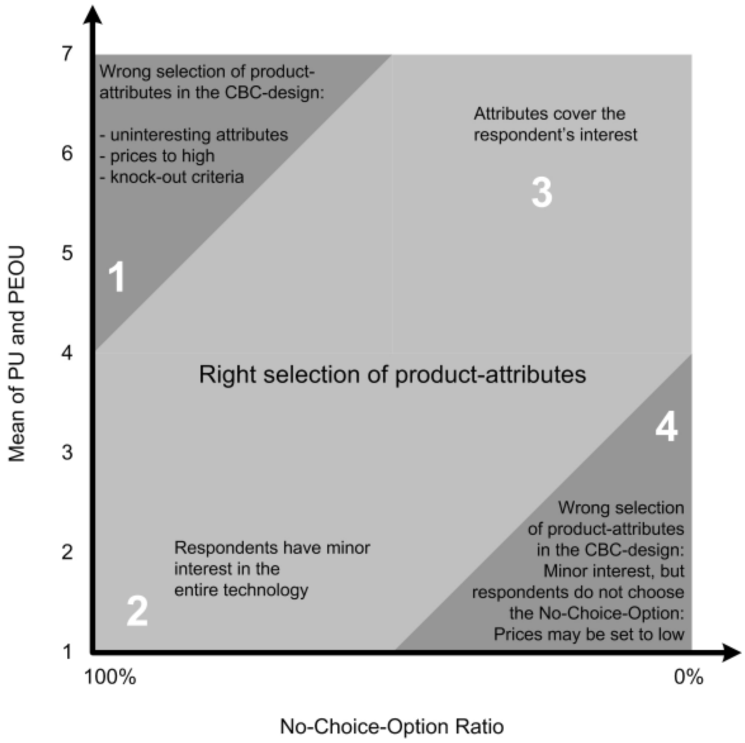

Figure 2: Comparison of the Mean of PU and PEOU and the No-Choice-Option Ratio.

Choosing the no-choice-option (i.e. having a high no-choice-option utility) can occur basically due to two different reasons (Dhar 1997): all displayed choice alternatives are not sufficiently interesting compared to the consumer's ideal or the attitude towards the entire technology is low and this is why the consumer does not choose any product alternative. Figure 2 combines the mean of the latent variable values of PU and PEOU with the ratio of chosen no-choice-options in the survey. A high no-choice-option ratio corresponds to a high no-choice-option utility and vice versa. Area 1 displays the case that the no-choice-option ratio is high and the latent variable values for PU and PEOU are also high. Thus the high no-choice-option ratio is not related to a negative attitude to the technology in general. Rather, the product attributes in the CBC-design seem to be not well-selected. Most likely, the price stimuli are inappropriate or knock-out criteria have been triggered. In contrast, a right selection of product attributes accompanied by a minor interest in the entire technology is characterized by a high no-choice-option ratio and low values for PU and PEOU in area 2. The ideal case of a right selection of the product attributes and a positive attitude towards the technology in area 3 comes along with a low no-choice-option ratio and high values for PU and PEOU. In this case the consumer is highly attracted by the choice alternatives and rarely ticks the no-choice-option. Area 4 represents a special case: although the attitude towards the entire technology is very low, the consumer decides to choose a product alternative in the CBC. This can be traced back to a wrong setting of the price attribute. The prices are set too small, so that even uninterested consumers will buy a product alternative. The deployment of our approach can identify these four fields and, thus, can give advice whether the CBC-design is well-selected.

EMPIRICAL STUDY

For verifying our model we conducted an online survey (April and May 2010) comprising both TAM and CBC models. The sample of 412 respondents (average age of 29) comprises a variety of German consumers with high and low intentions to use the presented technology in the future. Almost all consumers had no experience in the technology prior to this survey. The sample is not representative, since the primary goal is to demonstrate the applicability of our approach. Most respondents are young, internet-affine people (20 to 30 year old).

Subject of the study was a commercial bundle of a so-called web operating system [WebOS] (Messerschmidt and Lilienthal 2010; Weiss 2005). A WebOS is a desktop environment launched within a web browser similar to desktops of common operating systems. From technical perspective a WebOS is an interface of a virtual machine running on a cloud server. As a service delivered via the internet, it can be accessed from everywhere in the world and from every device given that an internet connection is available. The WebOS utilizes storage and computational power dynamically delivered by an external provider. A WebOS might even replace classical operating systems in the future. Then, PCs can be replaced by thin clients and mobile devices, since computing power is no more a critical property of the access device. WebOS as a technology is enabled and will be additionally forced by advances in ICT, namely high speed mobile internet and the spread of cloud computing. WebOS as a technology inherits all the popular benefits of cloud computing (Foster et al. 2008). Thus WebOS is a highly innovative, potentially ground-breaking technology. However, existing products and business models, e.g. Ghost Cloud Computing (Ghost Inc. 2010), EyeOS (EyeOS 2010) and icloud (icloud 2010) are still experimental and do not yet agree to the above definition on all points. Thus, it is extremely important for potential providers to know the preferences of potential customers. As the technology is brand new, we expect that perceptions play an important role in the utility of a product in addition to product attributes, which makes WebOS an excellent test object for our methodology. In the survey the product was presented as a commercial bundle including the WebOS, mobile internet connection with sufficient bandwidth and a client device for a monthly flat fee. In bundling the product, we can present the consumer an all-in-one product without any hidden extra costs.

As attributes for the CBC analysis we selected *performance* (clearly defined categories), *provider* (a potential brand), *operating system* (=WebOS), *minimum term* (reflecting contractual flexibility), and *price*. Because computational performance has lots of dimensions, we abstracted performance as three different classes (office, multimedia, games) very similar to performance classes one can find in the PC retailing market. Also, the operating system is extremely important for PC users, therefore we include the type of operating system as well (Windows, Linux, MacOS, other). The provider takes the role of a brand name. We expect the provider and its brand are associated with reliability, service quality etc. Since commercial products are not yet available, we test three different potential future providers: Amazon and Google as existing well-known cloud computing providers, T-Mobile as a large telecommunications provider, and a no-name start-up as no-brand baseline. The minimum term expresses the contractual flexibility, which is often cited as major advantage of cloud computing (Foster et al. 2008). The price (monthly flat fee) is set between 20€ and 50€, which has been identified as an appropriate price range in a pre-study.

We used an efficient design constructed by Sawtooth Software (http://www.sawtoothsoftware.com/) with 12 choice sets per consumer, each consisting of three alternatives plus the no-choice-option. Efficient designs guarantee that the small number of stimuli taken from the set of all product attribute level combinations yield a maximum of information without redundancy. The results of the MMNL estimation (first step) are shown in Table 1. All attributes are dummy-coded. The base level of each attribute is always fixed to zero and thus omitted in the table. The left hand column (heterogeneity mean) contains the mean of the coefficient across all respondents. A mean of zero does not coercively imply the absence of an effect, since the coefficients of the individual respondents may vary around zero, which is displayed by the corresponding standard deviation in the right hand column. The corresponding standard deviation of the coefficients expresses the heterogeneity across the respondents. A zero (or at least insignificant) value indicates no (significant) heterogeneity. The three price coefficients have unequal distances, which makes an alternative linear coding inappropriate. The no-choice-option utility is remarkably the one with the highest heterogeneity across consumers. Hence the no-choice-option covers most of the heterogeneity in the model with substantial impact on overall utility. The heterogeneity standard deviation of the no-choice-option utility is larger than the impact of all other attributes, hence considerable utility variance remains yet unexplained by the attributes. All attributes expose significant heterogeneity across consumers in at least one level. Operating system and performance also have much heterogeneity. This is not surprising since there is a strong segmentation in operating system preference; and performance preferences are also extremely segmented. Google as a potential provider is not regarded more valuable than any no-name provider, possibly due to negative news concerning privacy issues during and before conduction. Minimum terms of one month and three months show significantly higher utility than the baseline of 24 months. But among both there is no significant difference. The utility of price between 30€ and 50€ is almost linear, but between 20€ and 30€ it is half than expected accordingly. Conclusively, all estimates are extremely plausible.

Table 1: Results of the MMNL (first step). Significance levels: ***p<0.01; **p<0.05; *p<0.1

Attribute	Attribute Level (Dummies)	Coefficient (Heterogeneity Mean)	Coefficient (Heterogeneity Std. Dev.)
Performance (Base=Office)	Multimedia	**0.1452	***0.6197
	Games	*-0.1477	***1.0876
Operating System	Windows	***0.3864	***0.7748

(Base=Other)	MacOS	***-0.2552	***1.0805
	Linux	***-0.4659	***0.9561
Provider (Base=a startup)	Amazon	***0.2663	0.1192
	Google	0.0412	0.0835
	TMobile	***0.3471	**0.2534
Minimum Term (Base=24 Months)	1 Month	***0.5743	0.1468
	3 Months	***0.5073	0.0065
Price (Base=50€)	20€	***1.9539	***0.8781
	30€	***1.6030	0.0744
	40€	***0.7919	0.1115
No-Choice-Option		***2.1944	***2.3149

Table 2 shows the results of the linear regression of PU and PEOU (second step) on the no-choice-option utility. The construct PEOU is not significant in this study, which is sometimes reported in other TAM studies (Lee et al. 2003; Subramanian 1994), too. Subramanian (1994) stated that PEOU has less impact on the acceptance decision of an individual, when technologies are by their inherent nature easy to use. Since the handling of a WebOS does not differ significantly from a traditional operating system, it seems to be easy to use by nature, which may be an explanation for the insignificant effect of PEO in this study. We do not consider PEOU further because of its insignificance. PU has a negative effect on the no-choice-option utility as expected, i.e. the utility of the no-choice-option is low for consumers that perceive much usefulness of the technology. The coefficient of determination of 0.05 is rather small. Nevertheless, the estimated effect of -0.3 is rather strong in comparison with the utility effect (coefficients) of the CBC attributes.

Table 2: Results of the linear regression (second step), (dependent: no-choice-option utility in step 1).

Variable	**Coef.**	**Std. Err.**	**t-value**	**P>|t|**
PU	-0.3127	0.0722	-4.33	0.000
PEOU	0.0102	0.0794	0.13	0.898
Constant	3.4579	0.3845	8.99	0.000

Before we discuss the importance weights of the perceptions, we briefly demonstrate the application of the scheme in Figure 2, visualized in Figure 3. In this bubble-scheme scatter plot the size of the bubbles represents the number of consumers located in this area. The largest bubble represents 29 consumers. As in Figure 2, the x-axis represents the no-choice-option ratio out of the 12 choice tasks per consumer. Hence, 13 discrete values are possible on the x-axis. The mean of PU and PEOU is represented by the y-axis and the bubbles aggregate the rounded values. The upper left and lower right corners (areas 1 and 4) are sparsely populated, thus for only few consumers the attributes are inappropriate. Most consumers populate approximately the remaining diagonal indicating that the design of our CBC-survey is based on an appropriate selection of product attributes.

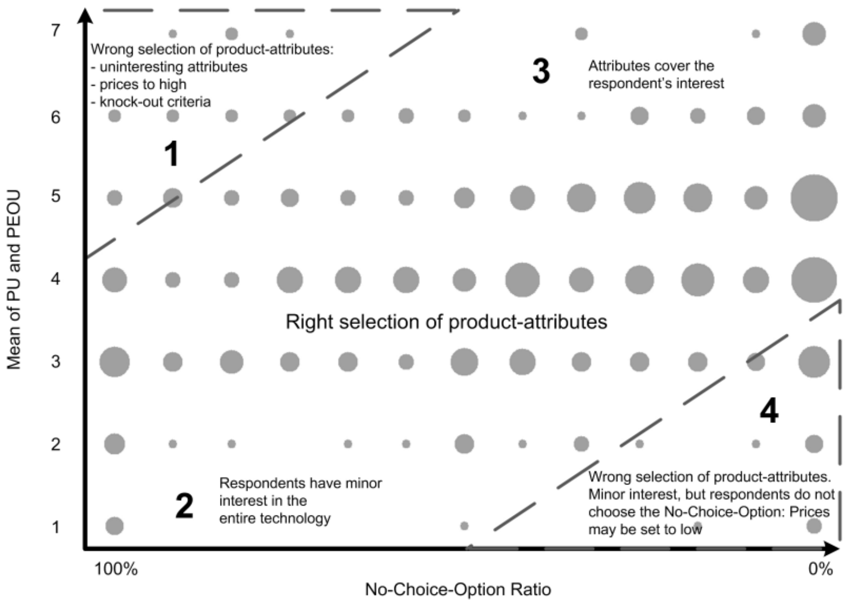

Figure 3: Empirical Comparison of the average of PU and PEOU and the No-Choice-Option Ratio.

The results of Table 2 tell that one scale point of PU lowers the no-choice-option utility by 0.31 or, accordingly, six scale points (best minus worst possible) lower the no-choice-option utility by 6*0.31=1.88. We have also computed the difference in utility between best and worst attribute level for all other attributes. These utility differences are the importance weights of the attributes by definition. Accordingly, we set 1.88 as the importance weight of PU. The results are displayed as percentages in Figure 3. We see that PU gains 27% of the total importance, which is more than of any other product attribute – even more than price, which is typically the most important one.

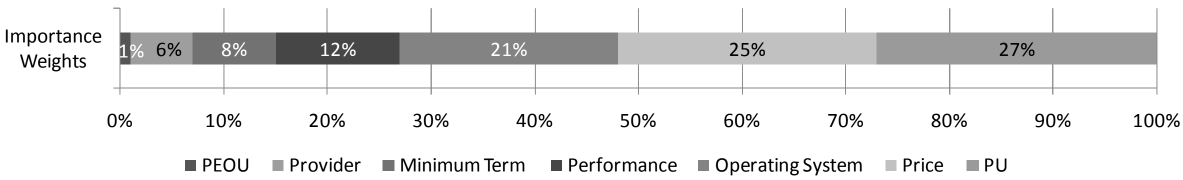

Figure 3: Importance weights as percentages.

CONCLUSION

In combining TAM and CBC we provide a valuable approach to consider latent variables in discrete choice models like the CBC. We find a domain where TAM can provide a valuable research contribution and help to overcome the limitations of the CBC for the practical deployment in market research for innovative technological consumer goods. We describe the utility of the no-choice-option by the perceptual constructs *Perceived Usefulness* and *Perceived Ease of Use*, which are well-grounded drivers of the attitude towards a new technology and the adoption intention in IS-literature. We can identify whether the consumer in a CBC refuses a new technology because he/she does not value the entire technology in general or because the selected product attributes in the CBC design do not yet meet the technical requirements consumers have: if the levels of PU or PEOU are small, the refuse is grounded in the low overall technology perception. If the levels are large, the refuse is due to wrong product attribute selection. And we can moreover quantify what a better perception of the technology would mean in terms of utility and whether it is worth to keep on investing in the development and promotion of the product. Our empirical results demonstrate impressively that the perception of the technology can potentially account for a considerable amount of utility, in our case 27%. For further research we suggest to completely exploit the scopes of CBC by transforming the estimated utilities into willingness-to-pay, which will be the next step on our research agenda.

REFERENCES

Ajzen, I., and Fishbein, M. 1980. *Understanding Attitudes and Predicting Social Behavior*. Englewood Cliffs, N.J.: Prentice-Hall.

Ashok, K., Dillon, W.R., and Yuan, S. 2002. “Extending Discrete Choice Models to Incorporate Attitudinal and Other Latent Variables,” *Journal of Marketing Research* (39:1), February, pp 31-46.

Bagozzi, R.P. 2007. “The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift,” *Journal of the Association for Information Systems* (8:4), April, pp 243-254.

Ben-Akiva, M., McFadden, D., Gärling, T., Gopinath, D., Walker, J., Bolduc, D., Börsch-Supan, A., Delquié, P., Larichev, O., Morikawa, T., Polydoropoulou, A., and Rao, V. 1999. “Extended Framework for Modeling Choice Behavior,” *Marketing Letters* (10:3), August, pp 187-203.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A., De Palma, A., Gopinath, D., Karlstrom, A., and Munizaga, M.A. 2002. “Hybrid Choice Models: Progress and Challenges,” *Marketing Letters* (13:3), August, pp 163-175.

Benbasat, I., and Barki, H. 2007. “Quo vadis, TAM?,” *Journal of the Association for Information Systems* (8:4), April, pp 212-218.

Brazell, J.D., Diener, C.G., Karniouchina, E., Moore, W.L., Séverin, V., and Uldry, P.F. 2006. “The No-Choice Option and Dual Response Choice Designs,” *Marketing Letters* (17:4), December, pp 255-268.

Brown, S.L., and Eisenhardt, K.M. 1995. “Product Development: Past Research, Present Findings, and Future Directions,” *The Academy of Management Review* (20:2), April, pp 343-378.

Cohen, S.H. 1997. “Perfect Union,” *Journal of Marketing Research* (34:1), February, pp 12-17.

Davis, F.D. 1989. “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology,” *MIS Quarterly* (13:3), September, pp 319-340.

Dhar, R. 1997. “Consumer Preference for a No-Choice Option,” *Journal of Consumer Research* (24:2), September, pp 215-231.

Ding, M., Grewal, R., and Leichty, J. 2007. “An Incentive-Aligned Mechanism for Conjoint Analysis,” *Journal of Marketing Research* (44:2), May, pp 214-223.

EyeOS 2010. “What is EyeOS?” Retrieved 2010/10/05, from http://www.eyeos.org/what-is-eyeos/overview/

Fishbein, M., and Ajzen, I. 2010. *Predicting and Changing Behavior: The Reasoned Action Approach*. New York: Psychology Press (Taylor & Francis).

Foster, I., Zhao, Y., Raicu, I., and Lu, S. “Cloud Computing and Grid Computing 360-Degree Compared,” *Grid Computing Environments Workshop*, Austin, Texas, USA, 2008, pp 1-10.

Freeman, C., Horsley, A., Jervis, V.T.P., Robertson, A.B., and Townsend, J. 1974. “SAPPHO Updated-Project Sappho Phase II,” *Research Policy* (3:3), November, pp 258-291.

Garcia, R., and Calantone, R. 2002. “A Critical Look at Technological Innovation Typology and Innovativeness Terminology: A Literature Review,” *Journal of Product Innovation Management* (19:2), March, pp 110-132.

Gefen, D., Karahanna, E., and Straub, D.W. 2003. “Trust and TAM in Online Shopping: An Integrated Model,” *MIS Quarterly* (27:1), March, pp 51-90.

Ghost Inc. 2010. “About Ghost Inc.” Retrieved 2010/10/05, from http://ghost.cc/home/about/

Green, P.E., and Srinivasan, V. 1978. “Conjoint Analysis in Consumer Research: Issues and Outlook,” *Journal of Consumer Research* (5:2), September, pp 103–123.

Green, P.E., and Srinivasan, V. 1990. “Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice,” *The Journal of Marketing* (54:4), October, pp 3-19.

icloud 2010. “No Clue? No Problem!” Retrieved 2010/10/05, from http://icloud.com/de/get-to-know

Kleinschmidt, E.J., and Cooper, R.G. 1991. “The Impact of Product Innovativeness on Performance,” *Journal of Product Innovation Management* (8:4), December, pp 240-251.

Lee, Y., Kozar, K., and Larson, K. 2003. “The Technology Acceptance Model: Past, Present, and Future,” *Communications of the Association for Information Systems* (12:50), pp 752–780.

Louviere, J.J. 1988. “Conjoint Analysis Modelling of Stated Preferences: A Review of Theory, Methods, Recent Developments and External Validity,” *Journal of Transport Economics and Policy* (22:1), January, pp 93-119.

Louviere, J.J., Hensher, D.A., and Swait, J.D. 2000. *Stated Choice Methods: Analysis and Applications*. Cambridge, U.K.: Cambridge University Press.

Louviere, J.J., and Woodworth, G.G. 1983. “Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data,” *Journal of Marketing Research* (20:4), November, pp 350-367.

Lucas Jr, H.C., Swanson, E.B., and Zmud, R.W. 2007. “Implementation, Innovation, and Related Themes Over the Years in Information Systems Research,” *Journal of the Association for Information Systems* (8:4), April, pp 206-210.

McFadden, D., and Train, K. 2000. “Mixed MNL Models for Discrete Response,” *Journal of Applied Econometrics* (15:5), September/October, pp 447-470.

Messerschmidt, C.M., and Lilienthal, M. “Acceptance of a Web OS as a Commercial Consumer Service Bundle,” *Proceedings of the 18th European Conference on Information Systems (ECIS)*, Pretoria, South Africa, 2010, pp 1-12.

Moore, G.C., and Benbasat, I. 1991. “Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation,” *Information Systems Research* (2:3), September, pp 192-222.

Myers, S., and Marquis, D.G. 1969. *Successful Industrial Innovations. A Study of Factors Underlying Innovation in Selected Firms*. Washington: National Science Foundation.

Paladino, A. 2007. “Investigating the Drivers of Innovation and New Product Success: A Comparison of Strategic Orientations,” *Journal of Product Innovation Management* (24:6), November, pp 534-553.

Rothwell, R. "Factors for success in industrial innovations from " in: *Project SAPPHO-A Comparative Study of Success and Failure in Industrial Innovation*, Science Policy Research Unit, University of Sussex, Brighton, 1972.

Scholz, S.W., Meißner, M., and Decker, R. 2010. “Measuring Consumer Preferences for Complex Products: A Compositional Approach Based on Paired Comparisons,” *Journal of Marketing Research* (47:4), August, p forthcoming.

Sivadas, E., and Dwyer, F.R. 2000. “An Examination of Organizational Factors Influencing New Product Success in Internal and Alliance-Based Processes,” *The Journal of Marketing* (64:1), January, pp 31-49.

Straub, D.W., and Burton-Jones, A. 2007. “Veni, Vidi, Vici: Breaking the TAM Logjam,” *Journal of the Association for Information Systems* (8:4), April, pp 224-229.

Subramanian, G.H. 1994. “A Replication of Perceived Usefulness and Perceived Ease of Use Measurement,” *Decision Sciences* (25:5-6), September, pp 863-874.

Temme, D., Paulssen, M., and Dannewald, T. 2008. “Incorporating Latent Variables into Discrete Choice Models-A Simultaneous Estimation Approach Using SEM Software,” *Business Research* (1:2), December, pp 220-237.

Train, K.E. 2009. *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.

Venkatesh, V., and Bala, H. 2008. “Technology Acceptance Model 3 and a Research Agenda on Interventions,” *Decision Sciences* (39:2), May, pp 273-315.

Walker, J., and Ben-Akiva, M. 2002. “Generalized Random Utility Model,” *Mathematical Social Sciences* (43:3), July, pp 303-343.

Weiss, A. 2005. “WebOS: Say Goodbye to Desktop Applications,” *netWorker* (9:4), December, pp 19-26.

Wu, I.-L., and Chen, J.-L. 2005. “An Extension of Trust and TAM Model with TPB in the Initial Adoption of Online Tax: An Empirical Study,” *International Journal of Human-Computer Studies* (62:6), June, pp 784-808.