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STANDING BETWEEN PURCHASE INTENTION AND ACTION: PRODUCT VALUE AND ITS UNCERTAINTY

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Abstract

This study examines the decision-making process of customers focusing on how purchase intention is transformed into actual purchase. Specifically, we investigate 1) how purchase intention is formed, 2) how purchase intention drives action, and 3) what factors stand between purchase intention and action. After reviewing literature on purchase intention and action, and the product evaluation mechanisms employed by the customer, we propose the following hypotheses. First, product value has a positive impact on purchase intention (H1). Second, purchase intention increases the probability of purchase (H2) and third, the relationship between purchase intention and purchase will be moderated by uncertainty levels in product valuation (H3). To validate, we conduct a survey regarding four types of products and collect data from 300 respondents. Regression and Probit analyses methods are used for validation. H1 and H2 are supported while H3 is partially supported. This study challenges the conventional notion that customers with high purchase intentions will necessarily move to the purchase stage. To this end, we examine the relationship between purchase intention and purchase, and find that uncertainty in valuation moderates the relationship.

Keywords: purchase intention, product value, uncertainty, regression analysis, probit analysis, Parallelism test.

1 INTRODUCTION

The purchasing behavior of online consumers has been one of the primary topics in Information Systems (IS) research. It is a base measure of sales, revenue, and profit of online businesses (van der Heijden et al. 2003) and determines business success subsequently. Constructs, such as customer satisfaction and loyalty, have been considered important in IS studies because they are the factors that promote customer purchase (Ha et al. 2010).

Given the importance of purchasing behavior, numerous IS studies have attempted to predict customer buying behavior in various contexts (Kim et al. 2008). In most of these studies, however, purchase intention and not actual purchase was measured, deriving from the assumption that high purchase intention leads to customer purchase. Well known theories such as the theory of reasoned action (TRA) and theory of planned behavior (TPB) confirm the strong correlation between intention and action (Werner 2004).

In reality, however, inconsistency between purchase intention and actual purchase often exists. For example, online shoppers occasionally forgo purchase even though they desire a particular product (BBC 2009). They hesitate to pay the price at the last moment of transaction, so that final behaviors frequently do not correspond to original intentions. Customers may fear to have transaction through online because online shopping is non-experiential, that is, people cannot see or touch a product.

The inconsistency between purchase intention and actual purchase in online business is worth examining because of the critical impact of purchase, not purchase intention. If there are factors that prevent highly interested customers from making an actual purchase, they should be identified and investigated.

Therefore, the present study examines the decision-making process of customers by focusing on how purchase intention is transformed into actual purchase. Specifically, we investigate 1) how purchase intention is formed, 2) how purchase intention drives action, and 3) what factors stand between purchase intention and action. To these ends, we first review relevant literature on purchase intention and action, as well as the product evaluation mechanisms employed by the customer. We develop a research model of purchase intention and action, along with hypotheses on customer behavior. To validate the proposed model and hypotheses, we analyze the results of the survey on online shoppers. A discussion of the contributions and implications of our results concludes the paper.

2 THEORETICAL BACKGROUND

2.1 Behavioral Intention, Behavior, and Perceived Control

Theories such as the TRA advocate the widely held assumption that strong purchase intention leads to high probability of customer purchase (Ajzen & Fishbein 1975). Highlighting the tendencies of human behavior, the theory proposes that "if a person intends to do a behavior then it is likely that the person will do it." From this perspective, purchase intention has been considered a definite precursor to and reliable determinant of purchase in numerous IS studies, which have measured purchase intention to predict customer purchase (Everard & Galletta 2006).

The TPB was later proposed as an extended-argument to the TRA, alerting the research community to the fact that behavioral intention not always leads to actual behavior when there is incomplete control over an individual's behavior (Notani 1998). "Perceived behavioral control (PBC)" was incorporated into the TPB as a new component to cover non-volitional behaviors for predicting behavioral intention and actual behavior. PBC is defined as a person's belief on how easy or difficult the consummation of a particular behavior is likely to be. In general, beliefs about resources and opportunities maybe viewed as an underlying PBC (Ajzen & Madden 1986).

Since then, PBC has been used to explain why not all individuals with high purchase intentions behave in the same manner in IS studies. For example, perceived transaction risk is regarded as a PBC because of the implicit uncertainty of the e-commerce environment (Pavlou 2003). Moreover, perceived financial cost is considered one of the controls in mobile banking business (Luarn & Lin 2005). In summary, 1) customer purchase intention forms customer behavior, and 2) both intention and behavior are influenced by behavioral controls, such as transaction risks (Figure 1).

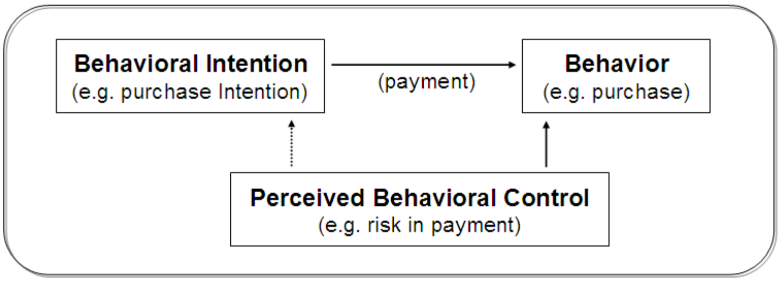

Figure 1. Relationship between Behavioral Intention and Behavior

2.2 Product Value Estimation

To precisely estimate the value of a product, customers require each product attribute, such as color, size, and design, to have acceptable quality. Customers then combine these attributes into one criterion of evaluation to estimate the total value of the product (Mukherjee & Hoyer 2001). However, product evaluation is inherently uncertain, especially in online shopping, because customers cannot see or touch the product. Although good sources of product information such as online customer reviews are available, customers can only estimate its value based on online information. Because of uncertainty, the estimation of customers on product value forms a distribution, that is, the nature of "estimation" is that it cannot be a specific, single number but a distribution of values with different probabilities, in contrast to definitive measurements (Figure 2).

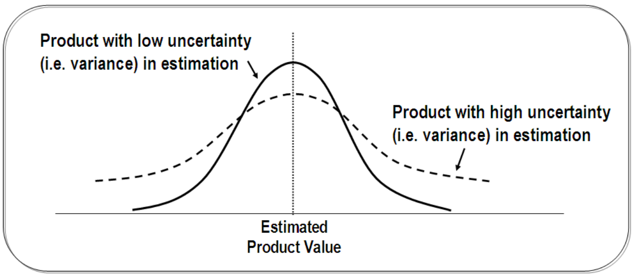

Figure 2. Product Value Distribution

When customers estimate product value and form a distribution of product value (PVD), statistically, the arithmetic mean (i.e., average of the distribution) shows the central tendency of data and would be *the expected value* (Varian 1992). However, in actual situations, this implies that when a customer buys a product, there is a fifty percent chance that product value is either higher or lower than his/her expectation.

The variance in distribution, on the other hand, shows how much the actual value varies depending on the product; that is, distribution variance pertains to the stability of actual product values. The larger the variance, the farther the actual value might be from the expected value. If the PVD reflects high variance, the worst product that a customer can possibly purchase will most likely be of substandard quality, whereas the best product will most likely be of excellent quality.

3 RESEARCH MODEL

3.1 Product Value, Purchase Intention, and Action

Customer purchase decision is made after careful examination of a product. Customers inspect various product attributes using different evaluation criteria and integrating them into one measure of product value. They then estimate the value of that product and use the estimation as basis for decision making. Therefore, product evaluation is naturally the primary and fundamental process in consumer decision making (Mukherjee & Hoyer 2001).

When evaluating a product, customers seek to be objective and rational so as not to regret their decisions. They fully utilize their knowledge and senses in making the right decision (Peracchio & Tybout 1996) and try to avoid impulse shopping (Madhavaram & Laverie 2004), which is also why they refer to all available information sources such as online reviews (Mudambi & Schuff 2010).

Based on the evaluation, customer purchase intention is formed. If a shopper finds a product attractive, high purchase intention emerges; if a product is unappealing, low purchase intention is formed. Given that evaluation is a cognitive and rational activity, purchase intention is also formed based on a customer's cognition, rather than emotion. Thus, for as long as the product values are high and the customer is rational, he/she is expected to have high purchase intentions. The positive effect of product value on purchase intention has been supported in various IS studies (Kuo et al. 2009). From this, we posit the following:

H1 – The higher the estimated product value, the higher the purchase intention.

The higher the intention, the higher is the probability of purchase. In the TRA and TPB, the causal relationship between purchase intention and purchase has been proposed and confirmed. Regardless of control factors such as gender or age, a customer is likely to purchase if he has high purchase intentions. Therefore, the intention to consummate a behavior is the immediate antecedent of that behavior.

Most IS studies that consider purchase intention as a dependent variable have also assumed the causality between purchase intention and purchase (van der Heijden et al. 2003). They measure purchase intention and identify its antecedents based on the assumption that high purchase intention represents actual purchase. From these, we propose the following hypothesis:

H2 – The higher the purchase intention, the higher the probability of purchase.

3.2 Uncertainty in Product Valuation

Although we put forward the positive association between behavioral intention and actual behavior (H2), we also observe many exceptional cases; high purchase intention not always leads to actual product purchase. For example, customers who estimate product value highly sometimes hesitate to buy the product (BBC 2009). Some customers give up purchasing altogether even though they truly want a product. A factor that prevents customers from purchasing a product at the last minute is not an unusual phenomenon.

A possible factor that reverses customers' initial intentions is the uncertainty in product valuation. When actual payment is imminent, customers begin to worry about the "possible bad luck" that they might encounter in their transaction. They form their purchase intention based on the estimated product value (i.e., average of the PVD). If a product generally appears of good quality, then customers would want to buy it. However, general impressions about a product do not affect customer perception of purchase transaction risk (i.e., when they pay); the possibility of suffering damage out of the transaction influences their final decisions. This phenomenon is decided by the variance in the PVD, called uncertainty.

The uncertainty (i.e. variance) in estimation represents the worst case scenario that a customer can possibly encounter during a transaction. For example, let us assume two products with the same expected value. Both have the same likelihood of having values higher or lower than the average (i.e., 50%). However, the product with higher variance will have a higher likelihood of being the substandard product, which may cause customers to become apprehensive. Consequently, wariness of purchasing the worst product (which has a value far from the expected one) sometimes drives customers to forgo purchase even though they are highly tempted to buy a product.

In electronic commerce, uncertainty in product evaluation is determined by the availability of product information on the web. If all the necessary information is readily available online, low uncertainty exists, and vice versa. For example, when people buy simple products such as a USB flash drive, all the necessary information including size and capacity can be accessed through the web. Thus, customers can easily and clearly evaluate the value of the product. However, when people buy products that require thorough evaluation, such as clothes, certain information such as texture and fit are simply difficult to deliver to the customers. Clothes therefore present higher uncertainty than does USB in customer evaluation. Search goods are examples of simple products, whereas experience goods are complicated commodities. In Lee and Lee’s work (2009), a detailed explanation on the product categorization based on uncertainty is provided.

In summary, customers are rational thus they use average value as base number when forming purchase intentions. However, uncertainty in evaluation affects customer behavior or purchasing because final decisions are influenced not by expected value but by the possibility of worst case scenarios. From these arguments, Hypothesis 3 is stated as follows.

H3 – Uncertainty in product value estimation negatively moderates the relationship between purchase intention and action.

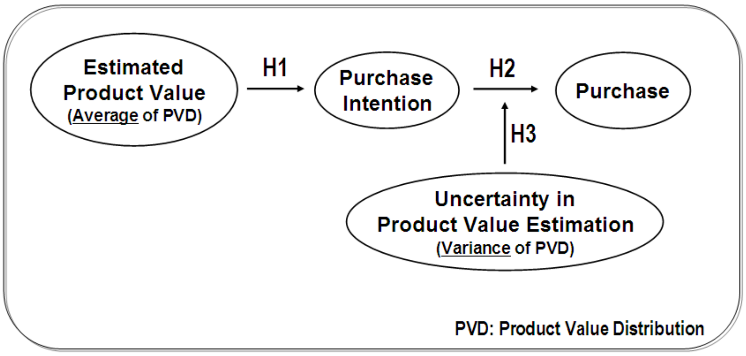

Figure 3. Research Model

4 METHODOLOGY AND ANALYSES

To validate the hypotheses, we conducted a web-based survey, described as follows. We showed respondents four types of products (monitor, netbook, package tour, and printer) with different levels of uncertainty and asked them to rate each product in terms of estimated value, purchase intention, and purchase action. In creating the questionnaires for product value, we referred to relevant literature and drew keywords such as *valuable, good, fine, useful* and *worthy* (Mukherjee & Hoyer 2001). We then constructed questions out of these keywords. For purchase intention, we adopted items from a previous study (Lee & Lee 2009). For product value and purchase intention, Likert scales were used.

For purchase action, we provided the respondents only two options: *buy* or *not buy* (details about questionnaire items are available upon request). The four products were then selected based on their uncertainty levels. The printer was designated as the product with the lowest uncertainty and the monitor, netbook, and package tour were accordingly designated in ascending order of uncertainty. All the products have similar pricing levels ranging from US$220−280. We collected data sets from 300 respondents. Table 1 shows no bias in gender and age. The shopping behavior of the respondents demonstrates that they are capable of understanding the context of the survey.

Gender		**Age**		**Online Shopping Behavior**	
Type	**Freq.(%)**	**Range**	**Freq.(%)**	**Occurrence**	**Freq.(%)**
Male	150 (50%)	19-29	73 (24.3%)	Seldom (once or twice)	25 (8.3%)
Female	150 (50%)	30-39	76 (25.3%)	Occasionally (from time to time)	132 (44%)
	300 (100%)	40-40	76 (25.3%)	Frequently	143 (47.7%)
		50-59	75 (25%)		300 (100%)
			300 (100%)		

Table 1. Descriptive Data Analysis

4.1 Factor Analysis

We conducted an exploratory factor analysis on four data sets to test convergent and discriminant validities. Furthermore, *Cronbach's alpha* was calculated to confirm the reliability of the items. As shown in Table 2, all items display adequate levels of convergent and discriminant validities and reliabilities.

	Printer		**Monitor**		**Netbook**		**Package tour**	
	C1	C2	C1	C2	C1	C2	C1	C2
PV1	**.856**	.319	**.893**	.305	**.902**	.329	**.873**	.401
PV2	**.903**	.331	**.856**	.406	**.905**	.322	**.857**	.457
PV3	**.897**	.320	**.888**	.369	**.885**	.383	**.862**	.441
PV4	**.875**	.317	**.828**	.428	**.814**	.489	**.795**	.542
PV5	**.883**	.358	**.820**	.476	**.830**	.473	**.782**	.571
PI1	.482	**.808**	.491	**.829**	.437	**.866**	.584	**.776**
PI2	.323	**.923**	.378	**.912**	.380	**.910**	.443	**.885**
PI3	.269	**.930**	.348	**.909**	.344	**.904**	.432	**.884**
Cronbach's α	**.968**	**.954**	**.970**	**.971**	**.976**	**.972**	**.980**	**.978**
PV: Product value; PI: Purchase intention Extraction method: principal component analysis; rotation Method: varimax with Kaiser normalization								

Table 2. Exploratory Factor Analysis and Reliability Test

4.2 Hypothesis Test

4.2.1 H1 & H2 Validation

Regression analysis was conducted on four cases to test H1. Table 3 shows that all the regression models are significant. However, the different beta coefficients in each product type show different effects of product valuation on purchase intention. Generally, a product with higher uncertainty indicates stronger impact of product value on purchase intention.

Probit analysis was performed for H2 because the dependent variable has binary values (i.e., buy or not buy). As in Table 3, all the probit models are significant, but the results also show that product with higher uncertainty levels lead to lower goodness of fit in model.

	H1 – Regression analysis			H2 – Probit analysis				
				Beta		Pearson's goodness-of-fit test		
Product type	Path coeffi.	T-value (Sig.)	R square	Coeffi.	Z-value (Sig.)	Chi-Square	df	Sig.
Printer	0.673	15.689 (0.000)	0.452	0.569	8.573 (0.000)	2.478	7	.929
Monitor	0.759	20.120 (0.000)	0.576	0.732	9.294 (0.000)	3.049	7	.880
Netbook	0.743	19.186 (0.000)	0.553	0.595	9.741 (0.000)	6.994	7	.429
Package Tour	0.863	29.497 (0.000)	0.745	0.425	8.906 (0.000)	13.452	7	.062

Table 3. H1 and H2 Test Results

4.2.2 H3 validation

H3 was validated by comparing the probit models tested in H2 among different product types using parallelism tests. Table 4 and Figure 4 show that except for the case 1 and 2, each product shows significantly different probit models that vary from those of the other products.

Comparison of Probit Models between	Parallelism test			Difference
	Chi-Square	df	Sig.	
Case 1: Printer – Monitor	2.303	1	0.129	N
Case 2: Printer – Netbook	0.000	1	1.000	N
Case 3: Printer – Tour	6.134	1	0.013	Y
Case 4: Monitor – Netbook	3.448	1	0.063	Y
Case 5: Monitor – Tour	20.496	1	0.000	Y
Case 6: Netbook – Tour	8.946	1	0.003	Y

Table 4. H3 Test Results

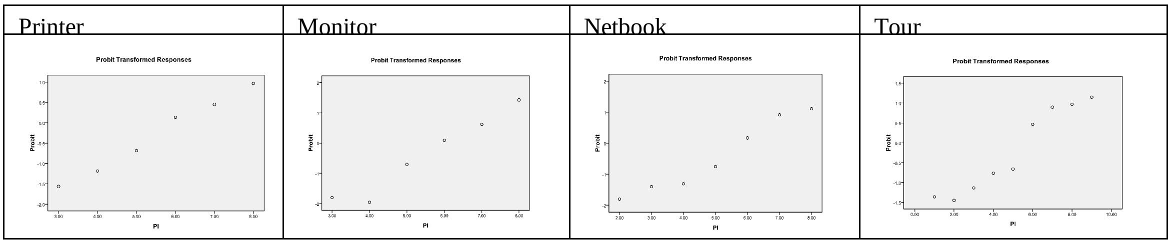

Figure 4. Probit Analysis Plots

5 DISCUSSION

5.1 Summary of Findings

The results of data analysis show that first, product value has a positive impact on purchase intention in all the products (H1 is supported). Second, purchase intention increases the probability of purchase in all the products (H2 is supported). Third, most of the probit models show significantly different beta coefficients between purchase intention and purchase according to uncertainty levels in product evaluation. The highest beta coefficient (0.732) in the probit model is exhibited by the computer monitor; the netbook yields a mid-level coefficient (0.595); and the package tour shows the lowest (0.425). Thus, H3 is partially supported, except in the case of the printer.

On the basis of these results, we further discuss the following observations: First, the impact of product value on purchase intention increases as uncertainty increases, whereas the impact of purchase intention on actual purchase decreases as uncertainty increases. For example, the beta coefficient of the package tour in H1 is 0.86, whereas its coefficient in H2 is 0.43. By contrast, the coefficient of the monitor in H1 is 0.76, whereas its coefficient in H2 is 0.58. These results show that even though customers are easily attracted by a product, uncertainty in product value estimation may deter actual purchase.

Second, the plot of probit analysis on the package tour (Figure 4) shows a distinctive disconnection between groups with high and low purchase intentions, indicating that a clearly liked and disliked product (such as the package tour) has a critical mass point for eliciting purchase. Customers who like the tour are highly likely to purchase it, whereas customers whose intentions are below the critical point do not purchase. For products similar to the tour package, increasing purchase intention to a level higher than the critical point is important. Otherwise, actual purchase may not easily occur.

5.2 Contributions and Implications

The present study challenges the conventional notion that customers with high purchase intentions will necessarily move to the purchase stage. To this end, we examine the relationship between purchase intention and purchase, and find that uncertainty in valuation moderates the relationship. If customers are uncertain about their assessment of a product—an uncertainty that stems from their wariness of worst case scenarios—they hesitate or even forgo purchasing the product. When customers form their purchase intentions before the payment stage, they are not thoroughly aware of the possible "bad luck and act" that may be perceivable when rational estimation is conducted. However, once purchase is realized, customers begin to consider all the possible cases that they can encounter during the transaction. This variance in all possible cases works as a controlling factor for risk-averse customers.

Another theoretical contribution of the study is that the study emphasizes the difference between the "expected value" and the "actual probability of obtaining a product that corresponds to the expected value" using statistical parameters. We note the fact that the actual purchase occurs only once for each customer, and the product's expected value is, in reality, difficult to realize for each customer. Instead, a customer is more likely to purchase a product with a value that is either worse or better than their expectations. Through the study, we conceptually differentiate the concept of uncertainty from the expected value using the distributions of product value estimation and their independent roles in customer decision making.

For practical implications, we highlight the importance of actual purchase. Although the business goal is actual purchase and not intention, most previous studies have focused on purchase intention and used it as the final construct (Verhagen & van Dolen 2009). Therefore, we re-examine the path from purchase intention to purchase and argue that uncertainty in product valuation may be the obstacle in that path. If this obstacle significantly blocks customers from purchase, then strategies for addressing such an obstacle is worthy of further investigation.

Finally, we propose and validate product categorization in accordance with uncertainty in valuation. In electronic commerce, product valuation has been one of the most significant challenges for customers because of the impersonality of web transactions. Uncertainty in valuation is a serious obstacle to sales promotion. Therefore, the results of this study can serve as reference for practitioners to have clear and accurate perspectives on uncertainty and help them reduce such uncertainties to increase purchase.

5.3 Limitations and Future Research

The limitation of the current work lies in product variety. We chose four widely used products with different uncertainty levels, but these are not representative of all the products that may be worth investigating. Future research can incorporate a higher number of products tested. Moreover, the high correlation between product value and purchase intention may require a different operationalization style. Conceptually, product value and purchase intention are different, but measurements still yield large overlaps. Such technical problems may be avoided by conducting pilot tests.

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