Consumers' Acceptance of Websites for Pre-Purchase Information Seeking

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Abstract

The Internet has been recognized as a critical communication tool between business and consumers. More and more consumers prefer to seek product related information on the web before making purchase decisions. However, much prior research indicates that commercial websites still suffer from low consumer acceptance rates. Consumers are either dissatisfied with the website functionalities or experience difficulty in locating needed information. We therefore propose to use the Website Acceptance Model (WAM) to account for consumers' acceptance of websites for pre-purchase information seeking. The WAM is based on theoretical concepts from the extended technology acceptance model (TAM) and incorporates concepts of task-technology fit (TTF) and the cost-benefit framework of pre-purchase information seeking. Specifically, we propose that product categorization (i.e. search goods vs. experience goods) serves as the contingency factor for the causal relationship between the constructs in WAM. The survey was conducted on 254 valid respondents. Results strongly support the base model of WAM and exhibit that product categorization is a critical contingency factor that has a significant impact on consumers' intention to use a website for pre-purchase information seeking.

Key words: Technology acceptance model, task-technology fit, experience goods, search goods, pre-purchase information seeking

消費前資訊搜尋之網站接受度

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摘要

網際網路是現今消費者與商家間溝通的重要媒介，越來越多的消費者希望在決定是否購買產品前，先在網站上作消費前的資訊搜尋；然而多數的研究結果顯示，消費者對於商業網站的評價與接受度是非常低的，消費者的不滿來自於網站功能的不足或是難以找到所需資訊。因此本研究試圖提出網站接受度模型，以探究消費者對於使用網站來做消費前資訊搜尋的接受度。網站接受度模型是以科技接受模型與科技適配理論為理論基礎，主要提出以商品種類 (例如: 搜尋性商品或經驗性商品) 做為此模型的調節變數，此外並結合成本效益架構來進一步解釋消費者在進行消費前資訊搜尋的行為。本研究採取實證研究法，總共回收254份有效問卷；分析結果支持本研究所提出的網站接受度模型，並且顯示商品種類為影響消費者做消費前資訊搜尋之非常重要的調節變數。

關鍵字：科技接受度模型、科技適配理論、經驗性商品、搜尋性商品、消費前之資訊搜尋

1. INTRODUCTION

With the rapid growth of today' knowledge-based economy, people heavily rely on the Internet to perform all kinds of information tasks, which include creating, retrieving, storing, and sharing information. In particular, the Internet has become one of the most important sources through which to seek product-related information. Product information seeking is one of the most common tasks people perform on the Internet and is also reported as one of the most important purposes of commercial websites (Brandt 2006; Han 2005; Katerattanakul 2002). Moreover, whether consumers can use information to improve their judgment ability and decision quality significantly affects the efficiency of the E-market (Kulviwat et al. 2004; Martin 2002). Therefore, it is essential for commercial website providers and the academic world to understand how a web site can effectively facilitate information seeking process. Our study takes a step in this direction by examining consumers' acceptance of a website for pre-purchase information seeking (PIS).

In the context of performing PIS online, consumers are exposed to a great amount of information provided by various marketing vendors. The Internet serves as a tool that allows businesses and consumers to communicate and exchange information without the limitations of time and space (Bakos 1991; Etemad 2004). Through this high-tech medium, businesses are free to advertise products and offer all sorts of information seeking functionalities to attract consumers to visit their website, as any visitor could be a potential customer (Haubl & Trifts 2000; Martin 2002). On the other hand, consumers acquire information from preferred websites and decide what information could help them make better purchasing decisions (Haubl & Trifts 2000). Hence, these commercial websites should ideally serve as one of the most efficient and cost-effective PIS tools for consumers.

However, many commercial websites suffer from low consumer acceptance rates (Dobie et al. 2001). Consumers are either dissatisfied with the website functionalities or have difficulty in locating the needed information (Dutta et al. 1998; Vezina & Militaru 2004). This could potentially drive away many business opportunities and eventually damage consumer perceptions of the business. Hence, it is critical to investigate the factors that lead consumers to accept and reuse a website. Increasing the depth of our understanding of this subject matter can help businesses better construct consumer-oriented websites and enable them to manage the websites more efficiently and effectively.

The remaining content of this paper is organized as follows. Section 2 discusses the research model and hypotheses that we proposed in this study. Section 3 describes the research methodology. Section 4 presents the results. In section 5 we conclude our work and present potential limitations and future research directions.

2. THEORY DEVELOPMENT

Differing from traditional methods, performing PIS in online environment consists not only of information seeking but also technology usage, which includes interacting with various technical functionalities aimed at enhancing the seeking experience. Therefore, our research model, the website acceptance model (WAM) for PIS, (See figure 1) is constructed based on theories which have developed in two areas. They are the (1) the technology acceptance model (TAM) (Davis 1989; Davis et al. 1989), which may be extended with constructs of task-technology fit (TTF) (Dishaw & Strong 1999), and (2) the cost-benefit framework of PIS. Besides the base model of WAM, we propose an important contingency factor, product categorization (i.e. search and experience goods). The empirical research results show that consumers demonstrate different information seeking behavior (including perceiving different degrees of risks, seeking for different kinds of information, relying on different kinds of information sources) for search and experience goods. Therefore, we propose that product categorization should act as a contingency factor in the hypothetical relationships between the constructs in WAM, as shown in Figure 1. The research model includes two parts: the base model of WAM and the contingency factor of product categorization.

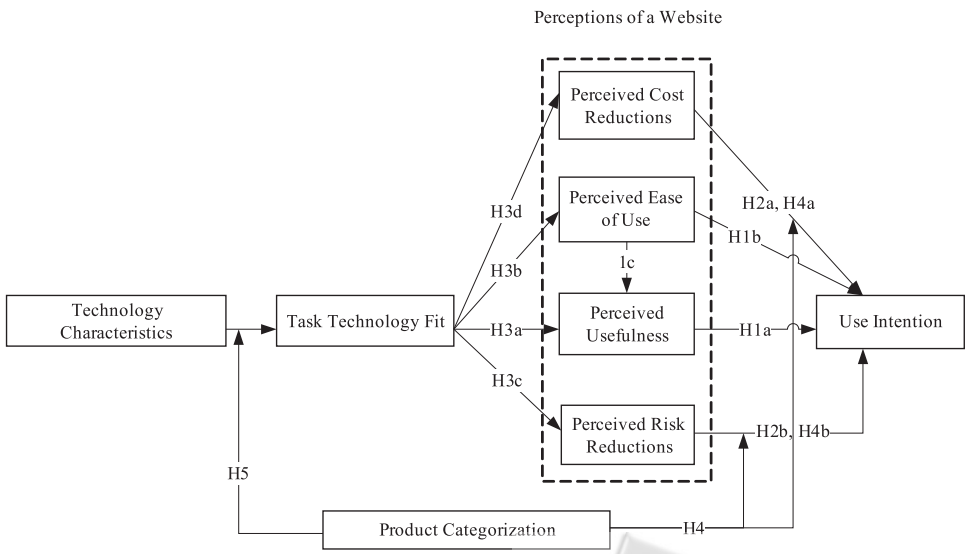

Figure 1: Website Acceptance Model for Pre-purchase Search of Product Quality Information

2.1 Technology Acceptance Model

The TAM has been widely used as the theoretical basis to account for user acceptance of new technology in many empirical studies (Chen et al. 2005; Liang & Yu 2005; Venkatesh et al. 2003). Given that it is not easy to distinct the construct of attitude from other concepts in

the model, some recent studies have simplified this model by deleting the attitude construct (Brown & Venkatesh 2005; Chau 1996; Hong 2002; Lu & Gustafson 1994; Ong et al. 2004). According to the TAM, user acceptance of new information technology (IT) is measured by user's behavioral intention to use. Perceived usefulness (PU) and perceived ease of use (PEOU) are two key factors that affect the user's intention to use the new technology. In the context of online PIS, PU is defined as the degree to which a consumer believes that using the website would enhance his/her performance in information seeking. PEOU is defined as the degree to which a consumer believes that using the website for information seeking would be effort-free.

Much prior research has empirically validated the TAM in organizational contexts (Adams et al. 1992; Venkatesh & Davis 2000). Recently, some researchers have applied it in the context of the Internet and found results congruent with the previous studies (Ong et al. 2004). Since information search is one of the common usages of the Internet, it is logical to hypothesize that consumers' PU and PEOU determine consumers' intention to use a website for PIS, as stated in H1a and H1b. Moreover, according to the TAM, PU is positively influenced by PEOU. Similarly, we hypothesize that PU is positively affected by PEOU in the context of performing PIS online, as stated in H1c.

H1: Perceived usefulness and perceived ease of use have a significant positive effect on consumers' intention to use a website for pre-purchase information seeking.

H1a: Perceived usefulness has a significant positive effect on consumers' intention to use a website for pre-purchase information seeking.

H1b: Perceived ease of use has a significant positive effect on consumers' intention to use a website for pre-purchase information seeking.

H1c: Perceived ease of use has a significant positive effect on consumers' perceived usefulness of a website for pre-purchase information seeking

2.2 The Cost-Benefit Framework of Pre-Purchase Information Seeking

Cost-Benefit framework has been empirically validated in multiple fields (Amir et al. 2000; Hess et al. 2006; Lee 2005). If applying the concepts of cost and benefit to PIS, consumers' intention to seek information is determined by two main factors: perceived benefits and perceived costs (Punj & Staelin 1983; Srinivasan & Ratchford 1991). Perceived benefits of PIS refer to the reduction of perceived risks through the seeking activities (Dowling & Staelin 1994; Kaplan et al. 1974; Mourali et al. 2005). Perceived costs of PIS refer to mental efforts, time, and financial costs (Nickols & Fox 1983). A consumer's ultimate goal is to obtain the maximum benefit from PIS while incurring minimum costs (Ekelund et al. 1995; Peterson & Merino 2003; Ratchford et al. 2003). As consumers have shifted their information seeking methods from traditional mediums to the Internet, results of empirical studies have shown that the actual importance of perceived benefits and perceived costs remained constant (Chen &

He 2003; Kulviwat et al. 2004). Similarly, in our research we propose to use perceived risk reductions (PRR) and perceived cost reductions (PCR) as the other two crucial factors to explain consumers' intention to use a website for PIS.

It should be noted that we propose to use perceived risk reductions (PRR) rather than perceived risks as the main factors that affect consumers' intention to seek information. When consumers are uncertain about the quality of a given product or unsure about their purchase decisions, they perform PIS with the hope of reducing the perceived risks to an acceptable level (Conchar et al. 2004; Cox 1967; Pavlou & Fygenson 2006). If seeking information on one website is not useful to reduce perceived risks, consumers refrain from further search and switch to other websites or alternative channels to seek for more useful information that may reduce their feeling of uncertainty (Kulviwat et al. 2004; Ratchford et al. 2003). However, if consumers perceive that the types of information provided on a particular website benefit them, they would continue their seeking activities on that website until they are satisfied. Therefore, it is not perceived risks per se that leads consumers to use or reuse a web site for information seeking. Rather, it is the degree of PRR that influences the use intention (Liebermann & Stashevsky 2002). The operational definition we give to PRR in this research is the difference between the perceived risks prior to and after information seeking has occurred.

In accordance with the arguments we raised above for PRR, we propose to use perceived cost reductions (PCR), instead of perceived cost, as one of the constructs in our research. Since the Internet is one of the alternative information seeking channels for consumers, if the information seeking costs are too high on the website relative to other media or other websites, he/she will switch back to traditional search media or move on to other websites (Kulviwat et al. 2004; Liebermann & Stashevsky 2002). Therefore, the operational definition of PCR here is the difference between perceived costs of search on the target website and other traditional media. If consumers are aware of the advantages and the cost reductions a website brings to them, it is logical to infer that consumers will adopt the website to pursue PIS activity. Therefore, the more PRR and PCR one feels, the stronger the use intention one experiences toward the website, which implies that PRR and PCR positively influence consumers' use intention on a web site for PIS. In conclusion, in addition to PU and PEOU, we propose that PRR and PCR also affect consumers' intention to use a web site in WAM.

H 2: Perceived risk reductions and perceived cost reductions affect consumers' intention to use a website for pre-purchase information seeking.

H2a: Perceived risk reductions have a positive impact on consumers' intention to use a website for pre-purchase information seeking.

H2b: Perceived cost reductions have a positive impact on consumers' intention to use a website for pre-purchase information seeking.

2.3 The Task-Technology Fit Theory

Besides TAM, one other widely used model in the MIS literatures is the task technology fit (TTF) model (Zigurs & Buckland 1998). Although these two models offer different perspectives of IT utilization, Dishaw and Strong (1999) have proposed to integrate these two models. Following their lead, we propose to incorporate the concepts from TTF into TAM and use the integrated concepts as the base model of WAM in this research. As the original TAM focuses more on the users' attitude/perception toward a particular IT, we believe antecedents of users' perception should not be neglected and can be explained by the concepts of TTF, which focuses on the match between user tasks and available functionalities of the IT.

TTF is defined as the degree of match between characteristics of tasks and technologies (Zigurs & Buckland 1998). In the context of performing PIS online, consumers' main goal is to spend the least effort and time to acquire useful information that can assist them in making purchasing decision (Ekelund et al. 1995; Peterson & Merino 2003; Ratchford et al. 2003) If the functionalities match with their information seeking tasks, then consumers should have a more favorable perception (i.e. PU, PEOU, PRR, and PCR) toward the website (D'Ambra & Wilson 2004) On the other hand, if the functionalities of the website do not match consumers' needs, their perceptions of the website should thus be negatively affected. This suggests that the degree of TTF between PIS and the technology characteristics affects consumers' perception of a website, meaning that it has a positive impact on consumers' PU, PEOU, PRR, and PCR, as illustrated in the following hypotheses.

H 3: Perceptions of a website are positively influenced by task-technology fit.

H3a: Perceived usefulness is positively influenced by task-technology fit between the information seeking tasks and the technology characteristics deployed on the website.

H3b: Perceived ease of use is positively influenced by task-technology fit between the information seeking tasks and the technology characteristics deployed on the website.

H3c: Perceived risk reductions are positively influenced by task-technology fit between the information seeking tasks and the technology characteristics deployed on the website.

H3d: Perceived cost reductions are positively influenced by task-technology fit between the information seeking tasks and the technology characteristics deployed on the website.

2.4 Contingency Factor: Product Categorization

Up to this point, we have generalized that PIS is one generic task and propose a base model of WAM for PIS online. However, much prior research indicates that consumers conduct information seeking differently for different kinds of products. (Dowling & Staelin 1994; Ekelund et al. 1995) Therefore, we want to further investigate how product categorization affects the process of PIS online and its role in WAM.

According to Nelson (1971, 1974, 1976, 1981), products can be categorized into two types:

search goods and experience goods. When the qualities of the product can be verified before use, the product is considered as a search good. When the qualities of the product can only be verified after use, the product is considered as an experience good. The results of previous empirical studies show that consumers demonstrate different information seeking processes for search goods and experience goods (Beatty & Smith 1987; Jacoby 1984) We summarize their findings in the following three points.

First, consumers seek for different kinds of information for search and experience goods. When seeking for information for search goods, consumers focus more on the "intrinsic cues", such as product specifications and factual information (Ekelund et al. 1995; Olson 1977; Olson & Jacoby 1972). On the other hand, when seeking for information for experience goods, consumers pay more attention on the "extrinsic cues" or soft information, such as brand names or other people's opinions (Olson 1977; Olson & Jacoby 1972).

Second, consumers perceive different degrees of risk toward these two product categories (Ford et al. 1990; Nelson 1970; Nelson 1976; Nelson 1981). For search goods, since product qualities can be verified based on product specifications (e.g., computer specs), people are less skeptical of the product qualities claimed by the seller. Hence, lower perceived risks are associated with the product quality claimed by the website for search goods. In the case of experience goods, product qualities claimed on websites are more difficult to verify, especially before consumption. Therefore, higher perceived risks are associated with experience goods.

Third, consumers rely on different sources of information for search goods and experience goods. Previous research has shown that the choice of using formal information sources is reversely related to the level of risk consumers perceive (Bansal & Voyer 2000; Dowling & Staelin 1994) When seeking for information on search goods, which have lower perceived risks, consumers are more likely to rely on formal information sources (e.g., commercial website of seller). On the other hand, when seeking for information on experience goods, consumers tend to believe that informal information sources (e.g., opinion leaders or word of mouth) may better reduce their uncertainty about the product.

In conclusion, consumers perform PIS very differently for search goods and experience goods. In the case of search goods for which product qualities can be verified before consumption, consumers perceive a lower degree of risks and are more likely to seek for factual information from the formal information sources. On the other hand, consumers perceive a higher degree of risk and are more likely to seek for soft information from informal information sources because formal and intrinsic product information are not as useful in helping verify the quality of experience goods (Bansal & Voyer 2000). As seeking activity shifts to the Internet, it is logical to infer that consumers would still perform PIS differently online for search and experience goods. Therefore, we propose product categorization should serve as a contingency factor in WAM. In particular, the contingency effect of product categorization is illustrated in the WAM through the two following areas: 1) The first effect could be observed between

consumers' perception of a website and use intention; and 2) another effect could be inspected between technology characteristics and TTF (see figure 1).

2.4.1 Product Categorization and Perceptions of a Website

Stigler (1961) and Farley (1964) have suggested in their research that information seeking is a balancing process between perceived costs and perceived benefits. As discussed in the previous text, perceived risks are low for PIS in the case of search goods. This means the factor that concerns consumers during the PIS process for search goods is perceived costs. Consumers focus on the factual information which will help them better verify the quality of search goods and are therefore eager to seek the maximum amount of useful information in the shortest period of time (with the intention of lowering the perceived costs). This implies that consumers should be more concerned about PCR than PRR for search goods.

In the case of experience goods, product qualities claimed on websites are more difficult to verify, especially before consumption (Nelson 1970). This means consumers perceive risks are higher. For experience goods, consumers do not seek more factual information to decrease perceived risks. Instead, they pursue extrinsic cues from informal information sources to reduce their uncertainty about a product (Olson 1977; Olson & Jacoby 1972). This suggests that information seeking costs do not increase with the high degree of perceived risks during the PIS process. This also means that PRR, rather than PCR, should be the major concern for consumers when performing PIS for experience goods. Therefore, we hypothesize that PRR has a positive impact on consumers' intention to use a website when seeking information for experience goods.

The above discussion leads to the conclusion that PRR is more influential in consumers' use intention of a website when performing PIS for experience goods, whereas PCR is more important for search goods. This suggests that product categorization (i.e. search goods vs. experience goods) acts as a critical contingency factor in the relationship between perceptions of a website (i.e. PRR and PCR) and use intention.

H 4: Product categorization serves as a contingency factor that affects consumers' perception of a website and their information seeking intention.

H4a: Perceived cost reductions have a positive impact on consumers'use intention of a website when seeking product information for search goods.

H4b: Perceived risk reductions have a positive impact on consumers'use intention of a website when seeking product information for experience goods.

2.4.2 Product Categorization and Task-Technology Fit

In accordance with the contingency approach emphasized in WAM, TTF also stresses that different kinds of tasks require different sets of supporting technology characteristics (Pavlou & Fygenson 2006; Zigurs & Buckland 1998). As we have discussed above, product categorization leads consumers to focus on different kinds of information and use different kinds of

information sources. Stated simply, the information seeking tasks are different for search goods and experience goods. According to the concept of TTF, finding the best fit between the tasks and technology characteristics will positively affect consumers' perceptions toward the website. If a website does not differentiate product categories but provides the same type of technology functionalities for all products, perceived TTF will decrease and deteriorate consumers' perception toward the website.

Given that the Internet offers numerous powerful technology functions that could support PIS, it is essential for web designers to select the appropriate technologies that can best assist PIS for search goods and experience goods. Some technology characteristics of the Internet may be more helpful for one type of product than another (Hoffman & Novak 1996; Keeney 1999; Newhagen & Rafaeli 1996). For instance, functions of personalization and interactivity may better suit consumers who seek information for experience goods. These two functions can effectively provide consumers an informal channel to acquire extrinsic cues through exchanging experiences or opinions about the product with others. On the other hand, consumers are more likely to seek for factual information (e.g., specifications) from formal information sources for search goods (Ekelund et al. 1995). In this case, sufficient information and multimedia functions which allow consumers to inspect the product virtually should help consumers who seek information for search goods.

Even though some technology characteristics better fit certain products, there are fundamental technologies that are important for all kinds of product categories on the Internet. Previous research indicates that the three most important technology features on the Internet are privacy, spatial characteristics and temporal characteristics (Hoffman & Novak 1996; Keeney 1999). Consumers can browse for product information or compare product prices from different vendors on the web 24 hours a day without physically visiting each store (Hoffman & Novak 1996) Also the Internet allows consumers to visit a website as an anonymous user, which eliminates privacy concerns (Keeney 1999; Richmond 1996).

Besides the technologies we mentioned above, it may be argued that there are more technologies that can be used to enhance consumers' online information seeking experiences, either for search goods or for experience goods. In truth, we do not intend to focus our research on exhaustively examining which technology characteristics best match specific tasks. Our main purpose is to demonstrate how product categorization makes a significant contingent impact on the relationship between technology characteristics and task-technology fits on a website. We argue that different sets of technology functionalities should be deployed for different kinds of products, as stated in Hypothesis 5.

H 5: Product Categorization serves as a contingency factory that affects the relationship between task-technology fit and technology characteristics of a web site in the context of product information seeking.

3. RESEARCH METHODS

The respondents were recruited from five universities located in Taiwan. Differing from traditional survey methods, voluntary respondents were invited to the laboratory and were paid after they completed the survey in order to ensure a higher rate of response. Out of 272 distributed surveys, 245 were completed and counted as valid responses. Given that product categorization is the contingency factor in our research, we divided the sample into two sub-sample groups, the search goods sub-sample and the experience goods sub-sample.

The survey procedure consisted of three stages, filling out a questionnaire prior to PIS, performing PIS on an assigned web site and filling out a questionnaire after PIS. The pre-seeking survey included four components: (1) demographic information; (2) categorization of the assigned product; (3) perceived costs of the product prior to information seeking on the website (i.e. perceived costs associating with seeking information through traditional mediums, such as TV advertisement, pamphlets, newspaper, or radio); and (4) perceived risks of the product prior to performing PIS on the internet. The post-seeking section of the survey assessed all the theoretical constructs in this study. In addition, perceived costs and perceived risks were measured again after information seeking to calculate the PRR and PCR.

Six products were chosen to serve as test products for our study. Three criteria were used during the initial selection process: 1) Products had to be familiar to the respondents (college students) so that they would be able to judge whether a product was a search or experience good; 2) product prices had to be affordable to respondents; and 3) the price difference between products had to be limited on the grounds because price could affect respondents' perception of risks. The six chosen test products were tickets, pizza, flowers, stuffed animals, TV games, and restaurant meals. Moreover, twelve websites were selected from the Internet, with two websites for each of the six products to serve as test websites through which the respondents could perform PIS in the survey. Specifically, the two websites chosen for each product contained similar product information with different technology characteristics deployed so that the matching effects of product categorization and functionality could be assessed.

Each respondent was randomly assigned to one of the twelve web sites to perform PIS and answer questions in the survey. Responses higher than the average were categorized into an experience goods sub-sample and those lower than the average were categorized into a search goods sub-sample. Consequently, out of the 245 valid responses, 125 were categorized into the search goods sub-sample and 120 were categorized into the experience goods sub-sample. The demographic profile of these two sub-samples is illustrated in Table 1. The results showed these two sub-samples do not differ from each other in terms of distributions of gender and age

(Gender: $\chi^2_{(1)}=0.64$, $p<0.20$; Age: $\chi^2_{(5)}= 4.40$, $p<0.42$).

Table 1：Profile of respondents for search goods and experience goods sub-samples

Item		Search Goods	Experience Goods
Gender			
	Male	73(58.4%)	64(53.3%)
	Female	52(41.6%)	56(46.7%)
Age		20.49	20.13

4. RESULTS AND DISCUSSIONS

The empirical data collected from the survey were analyzed using Lisrel 8 to test the proposed hypotheses. Lisrel, which is a kind of confirmatory factor analysis (CFA), consists of two stages: measurement model and structural model. In the measurement model stage, three criteria are used: item reliability, composite reliability, and discriminant validity. In the structural model stage, the goodness of fit is used to evaluate if the model derived from the empirical data fits our hypothetical model, the WAM.

4.1 Measurement model analysis of search goods and experience goods:

Three measures were used to exam the reliability and validity of the proposed constructs: item reliability, construct reliability, and average variance extracted. A summary of item reliability is given in Table 2. According to a survey of 25 articles from 1992 to 2002, there is no definite rule for determining an interpretation cutoff for factor analysis (Pohlmann 2004). But analysts commonly use values between 0.3 and 0.6 for the factor coefficients (Pohlmann 2004). There are still some basic guidelines that can be used for choosing a coefficient cutoff. Hair et al. (1995) recommended that with a sample size of 350, the minimum factor loading should be 0.3; Hair et al. (1998) also recommended that with a sample size of 200, the minimum factor loading should be 0.4. Since our sample size is between 200 and 350 (N=245 in this study), we decided to use a coefficient cutoff between 0.3 and 0.4 and delete the measurement items that did not meet the recommendation.

As demonstrated in Table 3, the composite reliabilities of all the theoretical constructs were all above 0.60 and the composite reliabilities of average variance extracted were all above 0.50, after deleting the inappropriate measurement items. This shows that the convergent validity of these constructs in the WAM were adequate for both search and experience goods sub-samples. In the case of discriminant validity, the correlations between the measures of distinct constructs were compared against the correlations of the items within the constructs. A summary of the comparison results is shown in Table 4 and Table 5 for search and experience goods respectively. Most of the inter-correlations between constructs were smaller than the correspondent average variance extracted (89% for search goods and 80% for experience goods). This indicates high

discriminant validity for the measurement models of both search goods and experience goods sub-samples.

4.2 Structural Model analysis of search goods and experience goods:

Based on our hypotheses, product categorization was the contingency factor in the base model of WAM. This means the causal relationship between constructs should be different for search goods and experience goods. Taking this into account, we proposed two structural models, one for search goods and one for experience goods. Then we examined the goodness of fit for these two structural models individually and compared their differences.

A summary of the model fit measures of WAM for search goods and experience goods is shown in Table 6. It includes the values of the original models and modified models. All the fit measures after modification surpassed the recommended range. This suggests the goodness of fit for both structural models is adequate. The result also shows the overall difference is statistically significant based on multiple sample analyses ($\chi 2$ (103)= 221.48, p<.001). This suggests that the proposed contingency effect of product categorization may exist, indicating that hypotheses 4 and 5 are supported.

Table 2：Item reliability of the measurement items for search goods and experience goods (factor loading)

Index of Constructs	Search	Experience	Index of Constructs	Search	Experience
Task-technology Fit			Information Quantity		
TTF1	0.50	0.75	IQ1	0.48	0.35
TTF2	0.36	0.38	IQ2	0.67	0.56
TTF6	0.64	0.60	IQ3	0.79	0.71
TTF7	0.81	0.69	IQ4	0.83	0.85
FFT8	0.55	0.49	Multi-Media		
Perceived Ease of Use			MM3	0.55	0.53
PEOU1	0.62	0.61	MM4	0.76	0.76
PEOU2	0.61	0.61	MM5	0.59	0.71
PEOU3	0.86	0.76	Temporal Characteristics		
PEOU4	0.86	0.71	TC1	0.50	--
Perceived Usefulness			TC3	0.59	0.61
PU1	0.59	0.64	Privacy		
PU2	0.52	0.48	Pr1	0.92	0.72
PU3	0.67	0.69	Pr2	0.61	0.59
PU4	0.81	0.76	Pr3	0.42	0.31
PU5	0.81	0.76	Spatial Characteristics		
PU6	0.79	0.67	PC1	1.10	0.64
Use Intention			PC2	0.61	0.88
UI1	0.88	0.79	Personalization		
UI2	0.92	0.90	Ps1	0.44	0.50
UI3	0.81	0.76	Ps2	--	0.48

Index of Constructs	Search	Experience	Index of Constructs	Search	Experience
Perceived Cost Reductions			Ps4	0.56	0.40
RPSC1	1.00	1.00	Ps5	0.64	0.61
Perceived Risk Reductions			Interactivity		
RPR1	0.44	0.38	I1	0.67	0.64
RPR2	0.86	0.79	I2	0.69	0.42
RPR6	0.37	--	I3	0.62	0.52
			I4	0.77	0.74
			I5	0.79	0.79

4.3 Effects of perceptions of websites

A summary of the Lisrel analysis of the direct, indirect and total effects on constructs is shown in Table 7. The results of the adjusted R2 in Table 7 indicate that 66% of the variance in consumers' use intention can be explained by the structural model of search goods and 72% of the variance in consumers' use intention can be explained by the structural model of experience goods. These results suggest that the constructs in the structural models provide satisfactory explanation for consumers' use intention of websites to perform PIS for both search goods and experience goods. Moreover, these results empirically demonstrate that consumers exhibit different information seeking processes for search goods and experience goods, which is consistent with the prior research (Beatty & Smith 1987; Jacoby 1984).

Table 3：Composite reliability and average variance extracted from both measurements

Construct	Composite Reliability		Average Variance	
	Search	Experienced	Search	Experienced
Perceived Ease of Use	0.89	0.88	0.67	0.64
Perceived Usefulness	0.91	0.91	0.64	0.64
Use Intention	0.92	0.91	0.79	0.78
Perceived Cost Reductions	- -	- -	0.99	0.99
Perceived Risk Reductions	0.75	0.77	0.51	0.64
Task-Technology Fit	0.84	0.84	0.52	0.52
Information quantity	0.87	0.86	0.63	0.61
Multimedia	0.84	0.87	0.73	0.7
Temporal characteristics	0.68	- -	0.5	0.7
Privacy	0.81	0.78	0.59	0.55
Spatial characteristics	0.87	0.87	0.78	0.77
Personalization	0.75	0.8	0.5	0.5
Interactivity	0.9	0.89	0.65	0.62

Table 4：Inter-correlations among study variables: Search goods

	1	2	3	4	5	6	7	8	9	10	11	12	13
1.TTF	**0.52**												
2. RPSC	-0.09	**0.99**											
3. RPR	0.25	-0.18	**0.51**										
4. PEOU	0.3	0.17	-0.1	**0.67**									
5. PU	0.82	0.21	0.11	0.54	**0.64**								
6. Use Intention	0.76	0.13	0.16	0.43	0.8	**0.79**							
7. Info. Quantity	0.71	-0.12	0.2	0.07	0.51	0.51	**0.64**						
8. Multimedia	0.36	-0.07	0.33	-0.01	0.3	0.29	0.62	**0.73**					
9. Temporal Ch.	0.56	-0.07	0.06	0.21	0.49	0.47	0.61	0.17	**0.5**				
10.Privacy	0.44	-0.03	-0.01	0.31	0.43	0.4	0.23	-0.04	0.66	**0.59**			
11.Spatial Ch.	0.13	-0.04	0.11	0.07	0.2	0.18	0.34	0.34	0.46	0.24	**0.78**		
12.Personalization	0.5	-0.09	0.23	0.09	0.46	0.43	0.75	0.71	0.6	0.29	0.65	**0.5**	
13.Interactivity	0.4	-0.07	0.19	0.1	0.47	0.43	0.56	0.57	0.53	0.31	0.51	0.77	**0.65**

Table 5：Inter-correlations among study variables: Experience goods

	1	2	3	4	5	6	7	8	9	10	11	12	13
1.TTF	**0.52**												
2. RPSC	0.09	**0.99**											
3. RPR	0.15	0.17	**0.64**										
4. PEOU	0.48	0.04	-0.07	**0.64**									
5. PU	0.77	0.08	0.02	0.53	**0.64**								
6. Use Intention	0.77	0.18	0.19	0.44	0.82	**0.78**							
7. Info. Quantity	0.81	0.12	0.11	0.31	0.62	0.66	**0.61**						
8. Multimedia	0.47	0.09	0.08	-0.01	0.39	0.43	0.71	**0.7**					
9. Temporal Ch.	0.44	0.07	0.06	0.34	0.55	0.46	0.57	0.49	**0.7**				
10.Privacy	0.29	0.03	0.03	0.45	0.41	0.31	0.27	0.12	0.76	**0.55**			
11.Spatial Ch.	0.17	0.06	0.06	0.03	0.27	0.26	0.5	0.42	0.6	0.2	**0.77**		
12.Personalization	0.65	0.09	0.08	0.19	0.52	0.52	0.72	0.69	0.54	0.12	0.62	**0.5**	
13.Interactivity	0.36	0.06	0.06	-0.06	0.28	0.31	0.53	0.76	0.33	-0.08	0.58	0.81	**0.62**

Note: The diagonals represent the average variance extracted

Table 6：Fit measures for search goods and experience goods

Indices	Standard	Search		Experience	
		Original	Modified	Original	Modified
χ^2/df	<3	2.35	1.14	3.12	1.64
GFI	>0.9	0.89	0.91	0.85	0.93
AGFI	>0.8	0.76	0.82	0.69	0.85
RMSR	<0.1	0.1	0.075	0.091	0.07
NFI	>0.9	0.88	0.9	0.86	0.92
NNFI	>0.9	0.85	0.92	0.82	0.94
CFI	>0.9	0.92	0.95	0.9	0.97

Table 7：Results of LISREL analyses

	Dependent Variables							
	Task-Technology Fit		Perceived Usefulness		Perceived Ease of Use		Use Intention	
Independent Variables	Search	Experienced	Search	Experienced	Search	Experienced	Search	Experienced
Perceived Usefulness			--	--	--	--	.60**	.57**
Perceived Ease of Use			.32**	.17**	--	--	[.19**]	[.10]
PRR			--	--	--	--	--	.13*
PCR			.24**	--	--	--	[.14**]	--
Task-Technology Fit			.67**	(.67**)	--	.54**	(.67**)	(.71**)
Internet Characteristics								
Information Quantity	.68**	.84**	[.46**]	[.56**]	--	[.45**]	[.46**]	[.60**]
Privacy	.33**	.14*	[.33**]	[.14**]	.35**	(.39**)	[.29**]	[.13**]
Space	-.17**	-.47**	[-.11*]	[-.31**]	--	[-.25**]	[-.11*]	[-.33**]
Time	--	--	--	.23**	--	--	--	--
Interactivity	--	--	.19**	--	--	--	[.12**]	--
Multimedia	--	-.27**	--	[-.23**]	--	(-.46**)	--	[-.22**]
Personalization	--	.50**	--	[.34**]	--	[.27**]	--	[.36**]
Adjusted R^2	0.57	0.82	0.81	0.61	--	0.33	0.66	0.72

*p < .05; ** p < .01; [ ] represents indirect effect; ( ) represents composite effect; without parenthesis represents direct effect.

4.3.1 Effects of Perceived Usefulness and Perceived Ease of Use

The results of Table 7 illustrate that PU significantly affects consumers' use intention of a website (β=0.60, p<0.01 for search goods, β=0.57, p<0.01 for experience goods). And slightly different from the anticipated outcome, PEOU does not have a direct impact, but has an indirect impact mediated through PU on consumers' use intention (β=0.19, p<0.01 for search goods and 0.10, n.s., for experience goods). This result is not surprising because the indirect relationship between PEOU and use intention has also been reported in many other studies (Chau 1996; Davis 1989), especially when the new technology is easy to learn. Same findings were also reported in Klopping and McKinney's study (2004) in the context of online shopping and online PIS. Similar to Klopping and McKinney's interpretation, PIS is a common usage on the Internet and users are more technologically savvy. Therefore, it is not difficult to understand why our results show that PEOU only has indirect effect on use intention. Possible explanation for the mediation through PU is that users pay more attention to the website usefulness than the website ease of use because it is easy to perform online PIS (Klopping & McKinney 2004). In conclusion, hypotheses 1a and 1c are supported and Hypothesis 1b is partially supported. In addition, the above results show an interesting contingent effect of product categorization on the relationship between PEOU and use intention. This suggests that PEOU has a significant impact on use intention for search goods, but not for experience goods.

4.3.2 Effects of perceived risk reductions and perceived cost reductions

Prior research indicated that PRR and PCR have impacts on consumers' information seeking behaviors (Punj & Staelin 1983; Srinivasan & Ratchford 1991). In our research, we further investigate how PRR and PCR affect consumers' PIS behaviors when seeking

for different kinds of product information (search v.s. experience goods). For search goods, the results show that PCR has an indirect impact, mediated through PU, on consumers' use intention (β=0.14, $p<0.01$). For experience goods, PRR has a direct effect on consumers' use intention (β=0.13, $p<0.05$). Therefore, hypothesis 2a is partially supported and hypothesis 2b is fully supported. Although the results are slightly different from what we expected, we are comfortable with the results shown only indirect relationship between PCR and use intention, mediated through PU. As mentioned earlier, consumers are less skeptical of the product qualities claimed by the seller for search goods because the product qualities can be verified based on the product specifications. Since consumers tend to believe in the information provided by the seller (low perceived risk), the remaining key concern consumers perceive should be the search cost. However, consumers could easily switch between the websites for the purpose of PIS without adding any financial cost. This means, consumers may not be so conscious about the PCR. Only if consumers are particularly aware of the usefulness of a website (i.e. consumers could always find useful information quickly and effort free on one website), the intention for consumers to use and even reuse the website will then be increased.

Most importantly, the results show that PRR does not have any effect on use intention in the case of search goods, and PCR does not have any effect on consumers' use intention in the case of experience goods. This means, PRR plays an important role in accounting for consumers' use intention in the case of experience goods, whereas PCR play a more essential role in the case of search goods. Again, we see the interesting contingent effect of product categorization. The results of PRR and PCR strongly suggest that product categorization (i.e. search goods vs. experience goods) act as the contingency factor for PIS online. Therefore, hypotheses 4a and 4b are fully supported.

4.4 Effects of TTF

As predicted, TTF affects consumers' use intention through both direct and indirect paths in the perception of a website. For search goods, the total effect of TTF on use intention is 0.67, with the direct effect being 0.27 ($p<0.01$) and the indirect effect being 0.40 ($p<0.01$) through PU. For experience goods, the total effect of TTF on use intention is 0.71, with the direct effect being 0.33 ($p<0.01$) and the indirect effect being 0.38 ($p<0.01$) through PU and PEOU. In conclusion, TTF influences consumers' use intention in two dimensions, the direct effect and indirect effect through PU and PEOU. The results show that hypotheses 3a is fully supported and 3b is partially supported. Different from Dishaw and Strong's study (1999), we obtained a strong relationship between TTF and perceived usefulness. The difference is possibly caused by focusing on different domain (workplace v.s. e-commerce). This result is congruent with Klopping and McKinney's (2004) study, which is also focus on e-commerce. Furthermore, our study detects different effects for different product categorization (search v.s. experience

goods), through PU and PEOU. Although TTF has no impact on PRR and PCR as we predicted in 3c and 3d, the overall existing evidence is strong enough to support that TTF is an important antecedent in perceptions of a website.

As mentioned earlier, we detected TTF creates different effects for different product categorizations. TTF has a significant direct influence on PU, both for search goods (β=0.67, $p<0.01$) and for experience goods (β=0.58, $p<0.01$). One interesting thing to note is that TTF does not have any impact on PEOU in the case of search goods, but has a highly significant direct impact in the case of experience goods (β=0.54, $p<0.01$). The possible explanation is that the task of PIS for search goods is already easy (product quality can be easily verified prior to consumption), and TTF has no further effect on PEOU. On the other hand, PIS for experience goods is more difficult because the product quality can only be verified after consumption. This gives scope for TTF to have an effect on and enhance the PIS experience with respect to PEOU. Once again, the contingent effect of product categorization is detected in the relationship between TTF and PEOU, even though this particular contingent effect is not included in our hypotheses. In conclusion, this part of research result successfully demonstrates how TTF affects consumers' perceptions of a website (PCR, PEOU, PU, and PRR). Understanding the antecedence of consumers' perceptions of a website can increase probability of designing a helpful website for PIS and furthermore enhance consumers' satisfaction in the electronic market.

4.5 Effects of Technology Characteristics

As discussed in the previous section, different sets of technology characteristics should be deployed to match with different tasks when performing PIS for search goods and experience goods, depending on the good. As shown in Table 7, we examined the effects of technology characteristics on TTF for search goods and experience goods. For search goods, the results show that TTF was affected by information quantity, privacy and spatial characteristics (β=0.68, $p<0.01$; β=0.33, $p<0.01$, β= -0.17, $p<0.01$, respectively). For experience goods, TTF was also affected by the characteristics mentioned above for search goods and, in addition, by two more characteristics, personalization and multimedia (β=0.50, $p<0.01$; β=-0.27, $p<0.01$). The results show that TTF is affected by different kinds of technology characteristics for search and experience goods. Once again these results match with prior research and empirically demonstrate that different kinds of tasks require different sets of supporting technology characteristics (Pavlou & Fygenson 2006; Zigurs & Buckland 1998). Similar to Pavlou's et al. study in 2006, we intended to investigate how different technological characteristics should be deployed to match with different tasks. Furthermore, our research demonstrated how product categorization leads consumers to focus on different kinds of information and exhibit different seeking behaviors (Beatty & Smith 1987; Jacoby 1984). Although some technology

characteristics proposed by us are not supported by the data, the results do show the contingency effects of product categorization and support our major argument that product categorization is a critical contingency factor that affects the impact of technology characteristics on TTF. Therefore, hypothesis 5 is supported. In conclusion, to achieve a positive perception of TTF, different sets of functionalities should be deployed for search goods and experience goods during the process of PIS.

5. CONTRIBUTIONS

Our research makes several significant contributions to both practitioners and researchers. On the academic side, our research makes the following contributions:

1. The research results confirm that PU and PEOU have a positive impact on consumers' intention to use a website for PIS. Moreover, PRR and PCR make significant impact on consumers' use intention as well.
2. Our research model – WAM is theoretically based on TAM and TTF with the incorporation of contingency concepts. Unlike most of the prior researches focusing mostly on consumers' perceptions, our research focus on both consumers' perceptions of a website and the antecedences, which are technology characteristics and search tasks.
3. The contingency factor of product categorization that we indicate in this research is especially important because it consistently exhibits effects on various relationships in the base model of WAM and, more importantly, offers a new perspective to the study of website acceptance.

On the practitioner side:

1. Our research demonstrates that product categorization is a critical contingency factor that has a significant impact on consumers' intention to use a website for PIS. Businesses need to be aware of the perceptions of their target customers and focus on providing appropriate information and technological functionalities based on different product categorizations.
2. Consumers carry different perceptions towards search goods and experience goods. For search goods, consumers perceive cost reductions more than risk reductions. For experience goods, consumers perceive the reverse. Businesses should be sensitive to the nature of product and deploy appropriate product information and technology characteristics to satisfy consumers' needs.
3. Consumers' perceptions of a website are positively influenced by the TTF. And the effect of TTF is affected by the match between technology characteristics and information seeking tasks of different kinds of products. Therefore, it is critical for business to understand the level of fit between technology and product categorizations.

Sometimes commercial websites may already offer enough useful functionality to increase the information seeking performance. However, due to improper arrangement or presentation, consumers either neglect or do not know how to use the functionality. We recommend businesses to place important functionalities that match the information seeking needs for search goods and experience goods.

6. CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

Recently some researches started to apply a modified TAM or TTF/TAM model to explain the technology adoption of e-commerce (Klopping & McKinney 2004; Pavlou & Fygenson 2006). Apparently the empirical results prove that these models are appropriate for the Internet environment. Therefore, our research decided to take a step further and conducted a detailed investigation on consumers' acceptance of a website for PIS. The base model of WAM, which incorporates the concepts of TAM and TTF, is supported by the empirical data of this research. Particularly, the contingency factor we included in this study, product categorization, exhibits a significant impact on the relationships between website use intention, consumers' perception of a website, and the antecedents. Product categorization is certainly a very critical contingency factor, but we would like to stress it may not be the only one; the level of its importance may change as surrounding conditions changes. The central idea here is to emphasize the importance of understanding consumers' use intention and the antecedents with a thorough consideration of contingency analysis. We hope our work will deepen our knowledge of consumers' behavior in electronic markets and inspire businesses to advance their management and technology usage in constructing a consumer-oriented web environment.

A few of limitations of this study should be noted. First, the findings and implications are obtained from students who are more experienced with Internet usage than average people. Thus, caution needs to be taken when making generalizations about these findings. Second, the websites we chose for the survey are existing commercial websites. Therefore, some of the technology characteristics found within the websites may not have been an exact fit for our research project. For example, most of the websites did not provide enough multimedia or interactive functions; the designing of an experimental website for the study may have yielded more dramatic results. Third, even though intention and behavior are highly correlated, this research only studied consumers' intention to use the website for PIS, rather than their actual behavior when using websites.

Further research needs to be conducted. First of all, this study only focused on consumers' intention to use a website but did not reflect actual purchasing power. Future research could focus on studying consumers' actual purchasing intention. Second, this research only focused

on studying commodities. As services provided on the Internet have become increasingly important, consumers commonly seek information about services rather than just commodities. Future research could investigate if PIS for services can also apply to the WAM model proposed here. Finally, our study only focused on search goods and experience goods. Another kind of product categorization called credence goods also exists, which is related to services. Future research could well extend into this area.

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