FIT DOES MATTER! AN EMPIRICAL STUDY ON PRODUCT FIT UNCERTAINTY IN ONLINE MARKETPLACES

Completed Research Paper

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ABSTRACT

This paper examines the antecedents and consequences of product uncertainty in online marketplaces by conceptualizing the dimensions of product uncertainty - description uncertainty (identifying product characteristics), performance uncertainty (inferring product's future performance) and fit uncertainty (matching product's characteristics with buyer's needs), with the focus on *product fit uncertainty*. It also theorizes the distinction, relationship, and effects of the three dimensions of product uncertainty. Finally, it proposes a set of IT artifacts to reduce product fit uncertainty.

The hypotheses are tested with survey and website transaction data from 274 buyers in Taobao, the largest online marketplace in China. The results first demonstrate the distinction between three dimensions of product uncertainty, show that relative to description and performance uncertainty, only fit uncertainty has significant effect on price premiums, satisfaction, product returns, and repurchase intentions, and support the effects of the use of IT artifacts, such as instant messenger, product forums, and decision support tools on reducing fit uncertainty. Implications for research, theory and practice are discussed.

Keywords:

Online marketplaces, product uncertainty, product fit uncertainty, computer mediated communication, decision support systems, price premium, product returns

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Introduction

Defects aren't even in the top three reasons for returns for products sold online, it's because difference in expectations. ---Mike Abary, Senior Vice President, Sony Inc., in *WSJ* 2009

IS researchers have long studied what prevents consumers from making purchases online (Dellarocas 2003; Li et al. 2009), and uncertainty was identified as one of the major hurdles due to spatial and temporal separation among buyers and sellers and buyers and products (Pavlou et al. 2007). The conventional wisdom regarding online shopping, is that consumers are haunted by seller uncertainty, thus academics and practitioners proposed several mechanisms to mitigate seller uncertainty in online marketplaces, such as institution-based structures (Pavlou and Gefen 2004) and feedback mechanisms (Dellarocas 2003).

At the same time, there is anecdotal evidence, expressed in the preceding quotes, that important as seller uncertainty was when Internet shopping was introduced, buyers' concerns about seller uncertainty have been alleviated with various transaction protection mechanisms in place, such as "eBay Buyer Protection". Recent surveys by the China Internet Network Information Center (CNNIC) reveal new insights in online marketplaces (CNNIC 2008). Experience goods – those that cannot be perfectly evaluated prior to purchase and use, such as clothes – are heterogeneous – they vary not only in quality but in size, color, style, design and texture as well. As most eCommerce textbooks suggest, experience goods are not ideal products for online sale becasue they are not standard, hard to describe, and difficult to evaluate. However, CNNIC (2008) shows that experience goods, such as clothes, are the top selling products in online marketplaces, exceeding search goods, such as books, computers, electronic appliances, and CDs. And contrary to conventional wisdom, in the US market, value of sales for clothing products sold via eCommerce reached 13,585 million dollars, surpassing computer hardware (11,097 million)[1], electronics and appliances (8,382 million), books and magazines (4, 200 million) or computer software (2,849 million) (Bureau 2009). This is despite the fact that current technology does not permit trying on clothes online. Buyer's dilemma in online purchases lies in the tradeoff between lower prices and greater selections versus higher product uncertainty about (experience) goods. And buyers' uncertainty prior to purchase may lead to negative price premiums, reduced customer satisfaction, increased product returns and lowered intentions to repurchase. On the one hand, companies are creating more and more niche products, which creates "long tails" in online markets (Anderson 2008). On the other hand, niche products that can potentially lead to riches (Brynjolfsson et al. 2006) have many unique attributes that make them difficult to evaluate. Statistics show online transactions to be only around 1% of total transaction value (Ministry of Commerce 2008). We posit that this is because in online environment, buyers are not able to get complete information about a product's descriptive information, how it will perform in the long term, and whether it matches their needs (herein referred to as product uncertainty). If the future online market is to become what Chris Anderson predicted - "sell less of more," (implying selling more customized products but less in each product category), we believe reducing buyers' product uncertainty, especially uncertainty about *fit*, will help make the long tail markets to function effectively and lead to that future.

In major media news reports, uncertainty about whether a product (or its characteristics) matches a buyer's needs (herein referred to as product fit uncertainty) in online shopping context has been a hot topic (ifeng 2010; TechCrunch 2010; WSJ 2008). However, in academic research, relative to the literature on seller uncertainty in online marketplaces (Gefen et al. 2003; McKnight et al. 2003; Pavlou and Dimoka 2006), product uncertainty in online marketplaces has not received equal attention. Product uncertainty, especially fit uncertainty, is rarely conceptualized, and often subsumed under the umbrella of seller uncertainty and even equated with it (Pavlou et al. 2008). Thus, we still have a weak understanding about the dimensions, consequences, and antecedents - how use of IT artifacts can help buyers reduce product uncertainty. Though there are several papers studying product uncertainty in offline market from the transaction cost economics perspective (John and Weitz 1988; Teo et al. 2004), the only paper we are aware of that conceptualizes product uncertainty in online marketplaces is Dimoka and Pavlou (2008), which delineates product uncertainty into two dimensions - description uncertainty and performance uncertainty, in the context of eBay Motors (one type of experience goods). We extend this line of literature by

[1] Up until 2005, value of sales for computer hardware is higher than that of clothing products.

studying a wide array of experience and search goods, and focus our attention on a new construct - product fit uncertainty.

To enhance our understanding of product uncertainty, especially fit uncertainty in online marketplaces, we study the following research questions:

- Are *description, performance and fit* distinct dimensions of product uncertainty?
- How do the proposed dimensions of product uncertainty relate to price premium, satisfaction, product returns, and repurchase behavior?
- How does use of IT artifacts in online marketplaces reduce product uncertainty?

For researchers, this study provides a comprehensive theoretical framework of the nature, antecedents, and consequences of product uncertainty with particular emphasis on product fit uncertainty. For practitioners, it helps understand how IT artifacts can be used to reduce product fit uncertainty in online marketplaces, to help online marketplace vendors set up optimum strategies to enjoy price premiums, increase customer satisfaction, prevent costly product returns, and promote repurchases.

Theory Development

Uncertainty in Online Marketplaces

The concept of "uncertainty" has been of interest to scholars in different fields, and defined differently across contexts. Duncan (1972) explained that uncertainty may arise from multiple characteristics that affect a party's uncertainty perceptions. Mainly two major types of characteristics - environmental uncertainty and behavioral uncertainty have been proposed (Rindfleisch and Heide 1997). Uncertainty can originate either from the environment (environmental uncertainty) or from the transaction partners in an economic exchange (behavioral uncertainty). Within this distinction, Pfeffer and Salancik (2003) defined environmental uncertainty as the degree to which the future states of the environment cannot be accurately predicted due to imperfect information, while studies that following Michael (1973) viewed behavioral (psychological) uncertainty to arise from the individual losing control of the environment. In the context of online marketplaces from the buyer's perspective, uncertainty arises either from the sellers or the products (shipping carrier is not the focus of this study thus it is omitted). This is because buyers cannot control or predict the behavior of sellers and they do not have perfect information of products.

The focus of this study - uncertainty in online marketplace - is innately an information problem. Prior scholars (Dellarocas 2003; Dimoka and Pavlou 2008a) have leveraged game theory and information economics theory to explain the behavior of online marketplace participants. Akerlof (1970) proposed signaling for markets with imperfect information, and it worked quite well for seller uncertainty and part of the product quality uncertainty issue. But as Stiglitz (2000) observed, "Akerlof ignored the desire of both some sellers and buyers to acquire more information. They did not need to sit passively by making inferences about quality from price (p1452, line 3)." We take a step further to address the information problem in online marketplaces – product uncertainty, with the special focus on a less studied construct - product fit uncertainty. And product fit uncertainty is what both buyer and seller wants to proactively mitigate before a transaction. Since for buyers, purchasing something does not fit entails return, or monetary loss (if return is impossible); for sellers, selling something that buyers do not really want entails disputes, product returns, and bad word-of-mouth.

Pavlou et al. (2007) defined buyer's uncertainty as the degree to which the outcome of a transaction cannot be accurately predicted due to seller and product related factors. Following Pavlou et al. (2007), uncertainty in online marketplaces arises from the complexity of the environment related to the sellers' behavior and the product's characteristics. Accordingly, uncertainty in online marketplaces is herein defined as the degree to which a buyer does not have complete information of the seller's future behavior (seller uncertainty) and the product's characteristics (product uncertainty).

The IS literature has implicitly assumed that seller and product uncertainty are part of a unitary construct, even if some recent work distinguishes between product uncertainty and seller uncertainty (Dimoka and Pavlou 2008b; Ghose 2008; Kim et al. 2009). Seller uncertainty arises from information asymmetry that prevents buyers from assessing the seller's behavior, while product uncertainty arises from information asymmetry or lack of interaction, which prevents buyers from assessing the product's characteristics. We herein focus on product uncertainty as it is an under-studied concept that merits further investigation.

Dimensions of Product Uncertainty in Online Marketplaces

We propose product uncertainty to have three distinct dimensions – a) *description*, 2) *performance*, and 3) *fit*, and theorize each dimension in the following discussions.

Product Description Uncertainty

Description uncertainty arises from the difficulty in assessing the product's characteristics, either due to the seller's intentional misrepresentation of the product or his inability to completely represent the product characteristics online. Description uncertainty is defined as the degree to which a buyer does not have complete information of the product's characteristics. Product description uncertainty is related to seller uncertainty since it is contingent upon seller's honesty and capability. A seller can take advantage of buyers by inaccurately describing the product, buyers' awareness of this could lead to their adverse selection in online marketplaces. On the opposite side, sellers can also reduce product description uncertainty by providing more detailed and accurate information to buyers with the help of various IT artifacts employed by online marketplaces.

Product Performance Uncertainty

Performance uncertainty originates from buyers' concerns about products' long-term performance defects, such as those for used cars examined by Dimoka and Pavlou (2008b). Performance uncertainty could be associated with negative price premiums, lower satisfaction with products, higher product returns, and lower repurchase intentions.

Product Fit Uncertainty

…venture capitalists even think that reducing uncertainty about product fit is the next big thing to address in eCommerce. ---*ifeng* 2010

The concept of *fit* has been studied in various contexts, such as organization strategy, business alignment, psychology and marketing. We first review extant literature on the concept of *fit* in individual psychology and organization behavior.

Vessey and colleagues (Vessey 1991; Vessey and Galletta 1991) studied human cognitive fit between information representation and tasks – also known as task-technology fit. It established that performance on a task will be enhanced if there is cognitive fit (match) between the information emphasized in the representation type and that required by the task type, and so long as there is a complete fit of representation, processes, and task type, each representation will lead to both quicker and more accurate problem solving. Applying the cognitive fit theory into our context, the relevant task is reducing uncertainty, and information representation types are website presentation, direct representation via communication and third party posts/ reviews in product forums. Though our research has similarities with task-technology fit, we do not assume variation in tasks, thus this line of theory is limited in application to this research.

On the other hand, in business alignment literature, Venkatrauman (1989) identified six perspectives of fit in the business strategy area. Although the domain of "fit" here is not about individual perception of "fit", the conceptualization is similar. Within the six perspectives proposed by Venkatrauman, *Fit as matching* is defined as the match between two related variables. In the setting of online marketplaces, fit as matching is closed related concept. Here Variable 1 is product characteristics, and Variable 2 is buyer's needs. Thus this line of theory will require us to measure the two variables separately. Notwithstanding the validity of this conceptualization and measurement of *fit* in strategic management, in our setting, buyer's (perceptual) assessment of fit (or uncertainty about otherwise) instead of the actual matching of the two variables is what matters. First, we are measuring the assessment of fit uncertainty before they purchase the product, instead of the actual fit of the two variables when they receive the product. Second, it does not matter whether the two variables are measured separately, as a buyer has the mental capacity to identify the degree of match without identifying needs and product characteristics separately, and the assessment of match is what we need to measure.

Recently, the issue of product fit uncertainty has been discussed and debated by academic researchers (Pavlou et al. 2008). However, important as it is, there is still no published work on product fit uncertainty in IS (Kim et al. 2009). It is widely accepted that uncertainty – be it seller uncertainty or product uncertainty- is an information problem. Uncertainty in online marketplace is also related to the quality and source of information, but most research treated information as "non-differential", overlooking that fact that same information can mean differently for different people, who may not only need different information, but may perceive the same information differently. A simple example here is that information in online marketplaces can be of high quality, but for different groups of people, even high-quality information may be equivocal: it may hold multiple, and often conflicting, meanings (Daft and Huber 1987; Daft et al. 1987). Different buyers are likely to have the same level of description uncertainty and performance uncertainty of products with certain amount of information, but their level of uncertainty about whether the product will *fit* their requirements could be highly different due to their own heterogeneous characteristics and specific needs. Offline buyers usually examine whether a product fits their needs by multiple times of physical interactions with the products of interest prior to purchase, e.g. trying on clothes, reading a book, drinking a coffee, etc. And they examine the quality of products, assess fitness of products and compare price offerings. This is especially true for experience goods, as compared with search goods. Experience goods have more attributes, and their attributes are more difficult to evaluate. While in the offline setting buyers are able to "kick the tires," buyers in online marketplaces can only read textual product information, or visually read the pictures to mentally image what products look like, and speculate whether the product will fit their requirements and tastes. Weathers et al. (2007) used the terminology "product performance uncertainty" to refer to product failing to fit consumer's needs or performing up to their expectations. Seemingly as it is measuring the construct of product fit uncertainty, from the measures it uses, it studies performance uncertainty (as conceptualized in this paper) instead of fit uncertainty.

Thus in this paper, we believe that product fit uncertainty arises because buyers cannot easily assess whether the products' characteristics match their requirements, tastes, and needs. It is herein proposed as a distinct dimension of product uncertainty. Product fit uncertainty is defined as the degree to which a buyer does not have complete information of whether the product's characteristics match her needs. This dimension of uncertainty results from lack of interactions between a buyer and a product.

It is established that information and knowledge about products can reduce uncertainty. However, not every piece of information is equal in reducing fit uncertainty. Only the information presented in a way that has "interaction" elements is relevant. For example, one may be unable to wear clothes online, but fit uncertainty can be reduced from asking a friend who she always shops with. One may argue that the process of fit uncertainty reduction is not static, it requires heuristics of the buyers. Buyers have deeper understanding of the product each time they interact with the product in some way. Though different buyers possess idiosyncratic way of finding the product that fit – some may prefer talking to a friend, others may prefer reading posts in a forum - they are constrained by the tools available online. Given the difficulty of direct interactions with products online given current technology, online interactions with products can be helpful in reducing product fit uncertainty, such as dyadic communication with people who have had direct interactions with the product, group discussions of product information mediated by online product forums, using decision support tools (or shopbots) provided by marketplace or third-party websites, reading real pictures (taken by the vendor instead of stock pictures) of the product taken from different angles and watching video presentations.

Consequences of Product Uncertainty

Researchers often use a related set of constructs to measure marketplace performance, such as price premium, consumer satisfaction, intention to repurchase and repurchase behavior. In this paper, we study actual product returns in addition to the above mentioned performance constructs. These constructs are important because improving these aspects can retain buyers and provide incentives to good sellers, thus reducing adverse selection and moral hazard issue, and maintaining effective and sustainable online marketplaces.

Price Premium

Consumers are willing to pay more for a clothing product when doing online shopping if they are convinced of buying what they have in mind. ---*Sina.com* 2009

There is rich literature in economics about information asymmetry and price premium. The information asymmetry literature shows that imperfectly informed buyers discount prices (Milgrom and Weber 1982; Shapiro 1982). Dimoka and Pavlou (2008b) used eBay Motors as a research context to study how buyers' perceived uncertainty impacts price premium, showing that product uncertainty is more influential than seller uncertainty.

We examine how the proposed dimensions of product uncertainty affect price premiums in online marketplaces by extending the information asymmetry literature. In markets with information asymmetry, buyers face uncertain products with hidden and often poor characteristics. Unless buyers are able to reliably differentiate between "good" and "bad" products, they are unlikely to give price premiums to good products, and they would value all products toward the average of both good and bad products (Shapiro 1982), giving rise to the "adverse selection" problem. Also, under prospect theory, buyers are generally prone to avoid uncertainty (Kahneman and Tversky 1979), and generally people in China have higher uncertainty avoidance index (UAI), than those in the United States (Hofstede 2001; Sia et al. 2009), thus they are likely to weigh the balance between product uncertainty and price. Rao and Bergen (1992) studied price premium of experience goods and search goods, and came to the conclusion that when consumer's quality consciousness (QC) is high – have good information about product quality (similar to lack of description uncertainty or performance uncertainty), they are less likely to offer price premium for search goods, while they still offer approximately same amount of price premium for experience goods. We argue that lack of interaction between a buyer and a product leads to product fit uncertainty, and that makes up the difference.

In online marketplaces, buyers are generally less likely to be certain about whether product characteristics will match their requirements before using the product. It was shown that people are willing to pay a higher price for a clothing product when the uncertainty about fit is reduced (Sina.com 2009). Dimoka and Pavlou (2008) also found that product description uncertainty and performance uncertainty are associated with negative price premiums for used cars (one type of experience good). On Taobao, there are myriads of products with attributes difficult to evaluate, buyers are generally willing to trade off product uncertainty with a higher price, especially experience goods. Extending Dimoka and Pavlou (2008), from description and performance uncertainty to include the proposed negative effect of product fit uncertainty on price premiums, we hypothesize:

H1: Price premium is negatively associated with a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

Satisfaction

Satisfaction has been extensively used by IS researchers as a measure for market performance (Bhattacherjee 2001; McKinney and Yoon 2002).The purchase decision made under high product uncertainty is likely to result in a delivered product that turning out to be a bad choice that had poor characteristics, probably performance defects, and characteristics that do not fit the buyer’s needs, thus leading to dissatisfaction. Thus, we hypothesize:

H2: Buyer satisfaction is negatively associated with a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

Product Returns

Buyers are likely to return a product if they are dissatisfied with the purchase, either because the product was incorrectly described (description uncertainty), it did not perform well (performance uncertainty), or it did not match their requirements (fit uncertainty). On the one hand, description uncertainty, performance uncertainty, and fit uncertainty indicate the level of knowledge about the products, buyers with less product uncertainty have more realistic expectations about how product look like, how it functions and whether it will be a fit, thus lowering the possibility of return when they receive and evaluate the actual product in person. Thus, we hypothesize:

H3: Product return is positively associated with a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

Despite proposing that all three dimensions of product uncertainty to have a negative effect on product returns, intuitively, one would argue that product defects or malfunctions account for the major reason of product return. However, news reports (WSJ 2008: in WSJ) show that defects aren't "even in the top three reasons for returns," as Mike Abary, senior vice president of SONY put it, the primary reason consumers return products is because they "didn't meet expectations." Consulting firms such as Accenture released reports (2008) on consumer product returns estimates that the average return rate for devices ranges from 11% up to 20%. The distribution of reasons to return the product is as follows: *68 percent: does not meet customer expectations; 27 percent: buyer's remorse; 5 percent: defects or malfunctions.* Besides, report from TechCrunch (2010) shows that pictures of adjustable mannequins wearing clothes increased sales three times and dramatically reduced returns by 28%. We expect that the gap between buyer expectation and reality could be reflected by product uncertainty, especially fit uncertainty.

Intention to repurchase

Behavioral intention is proven to be a good predictor of actual behavior (Ajzen 1985; Ajzen 1991). In IS research many studies have shown the link between intention to purchase and actual purchase behavior (Ou et al. 2008; Pavlou and Gefen 2004). A buyer’s uncertainty perception predicts her intention to repurchase because a buyer mostly wants to feel certain before a purchase. Thus, prior purchase with high uncertainty about product description, performance, and fit could negatively affect their intention to purchase from that seller again. Thus, we propose:

H4: Intention to repurchase is negatively associated with a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

Antecedents of Product Uncertainty

Information has value only when it reduces the uncertainty that pervades decision-making (King and Epstein 1976). In online marketplaces, information from different sources is available to help buyers reduce uncertainty about sellers and products in their decision making processes. Since seller uncertainty is an information asymmetry problem (Dimoka and Pavlou 2008b), following signaling theory (Spence 1973), seller information signals were used to reduce seller uncertainty, such as feedback score (Ba and Pavlou 2002), feedback text comments (Pavlou and Dimoka 2006), and third-party escrows (Pavlou and Gefen 2004). However, seller information signals cannot mitigate the uncertainty due to the difficulty in inferring product characteristics (description uncertainty), quality defects (performance uncertainty) and matching buyer needs with product characteristics (fit uncertainty). Four IT-enabled uncertainty mitigation mechanisms are proposed: *(1) Computer Mediated Communication (CMC), (2) User Generated Content, (3) Decision Support Systems (DSS), and (4) Rich website Product Presentation Formats.* These mechanisms are related to specific activities with the help of IT artifacts in online marketplaces: *(1) communication* *via IM, (2) viewing posts in online forums, (3) search and compare with shopbots, and (4) reading product information web pages.* These four mechanisms complement each other in reducing product uncertainty in online marketplaces.

Instant Messenger - Synchronous CMC

The theory of media richness argues that a medium's "richness" - i.e., its ability to change understanding within a time interval (Daft and Lengel 1986) - is determined by certain invariant fixed characteristics of the medium, such as *feedback speed, number of cues, degree of personalization, and language variety.* And both social presence theory and media richness theory argue that rich media or media with a high degree of social presence are better suited to ambiguous and equivocal tasks that require resolution of different views and opinions among people. Conversely, lean media are better for uncertain tasks that require the quick transmission of information and facts.

The seller's ability to describe the product's characteristics online is constrained by the relatively lean nature of the Internet interface. CMC has been seen as a useful method of interpersonal communication. Using experiments, Walther (1995) found that CMC groups achieved more positive results on several dimensions of interpersonal communication than did face-to-face groups. IM is considered a synchronous CMC tool, as it is "real-time" in nature (Jonassen et al. 1995). Functionally IM is usually considered a social networking tool, via which people connect with families and friends (Li et al. 2005), and colleagues (Cameron and Webster 2005). IM is also widely used in online C2C exchanges (Ou et al. 2008). By using instant messenger (IM), sellers are able to engage in direct communication with buyers to describe their products in a more detailed and personalized fashion. It is to the seller's best interest to describe the product's characteristics and provide more information than the website provides. And sellers can provide information about how the product performs in the long term by sharing their own and prior customers' experience.

On the other side, to reduce fit uncertainty, buyers need to infer the match between their needs and the product's characteristics. And sellers can match product offerings to buyer requirements by engaging in personal selling (Weitz and Bradford 1999). With personal selling via IM, seller caters to each buyer's need by matching her heterogeneous needs with the product's characteristics. While buyers cannot "kick the tires" in online marketplaces, it is possible to compensate for the physical separation between buyers and products with virtual personal selling with the aid of IM. With IM in online marketplaces, it is possible for sellers to engage in virtual personal selling to reduce buyers' fit uncertainty. Direct buyer-seller communication helps reduce fit uncertainty by helping buyers identify the product that fits them, which may also avoid psychological contract violation (Pavlou and Gefen 2005) since when buyers find the product more fit, they will think that the sellers have fulfilled their contract (psychological contract). On the other hand, it is impossible for a seller to cater to every buyer's needs with a website, since buyers are heterogeneous and there is not enough space to fully describe all product characteristics on her website. The buyer-seller communication is likely to result in customized sales advice, which could help customers better match their needs with products' attributes. The process also helps buyers learn the characteristics and functions of the product better, and helps create realistic expectations about what they are going to get. In online marketplaces, IM helps sellers cater to each buyer's needs by matching product characteristics with the buyers' needs with direct online communication, thus reducing fit uncertainty. From another perspective, when buyers are not sure whether the product fits their needs, they naturally resort to people who have purchased and experienced the product. According to social network theory (Wellman 1983), people with similar tastes are more likely to gather together. With IT artifacts, such as IM tools, buyers in online marketplaces has the capability to form social networks to share product and seller information. This information from computer-mediated communication is proposed to reduce product uncertainty. Thus, we propose:

H5: Communication via IM (between buyer and seller, and between buyers) is negatively associated with a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty

Online Product Forums – Asynchronous CMC and UGC

Online product *forums* (aka BBS) are discussion boards that facilitate buyer conversations about products. Similar to email, an online forum is considered an asynchronous CMC tool, as it is "delayed" in nature (Hiltz and Wellman 1997; Jonassen et al. 1995). Compared to direct buyer-seller communications, online product forums draw more people and opinions into the conversation, though most of the times it lacks real time feedback. Viewing posts in online product forums is shown to generate greater interest in the product category (Bickart and Schindler 2001), and online product forums are virtual discussion boards for people who share similar interests in a product. In product forums people post their experiences with the products they bought and used in text (threads and posts), and some buyers share pictures and even videos with forum members. Topics of typical product forums (such as Taobao product forum) include product attributes description (description and fit), long term performance defects issues (performance), and how much they like the products and why they like/dislike the products (fit). Thus, we hypothesize:

H6: Viewing posts on product forums reduces a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

Shopbots – A Form of DSS in Online Marketplaces

There are several decision support systems available in online marketplaces, such as vertical search engines, third-party product comparison tool, and other forms of shopbots (Smith and Brynjolfsson 2001). As buyers select desired product attributes, the shopbot generates a seller or product list; in this way, it helps buyers identify relevant sellers who offer the product that potentially matches their needs. Frictionless commerce as it might be in online markets (Brynjolfsson and Smith 2000), buyers still need to spend a lot of time and effort to evaluate whether a product fits their requirements, tastes, and needs. On the one hand, decision support systems compare different products and sellers and present information in an orderly manner, so buyers will have a better understanding of what products are available, their prices, and make the optimum choice that will satisfy their needs. On the other hand, decision support systems such as shopbot help overcome limitations inherent in human cognition and ensure that available information is used (Huber 1983; Zmud 1979). By identifying relevant information, decision support systems exempt buyers the process of initial searching and prescreening of relevant products, so they have more time and cognitive resources to examine the product's description information, evaluate product performance, and match the product characteristics to their own needs. Thus, we hypothesize:

H7: Use of shopbots is negatively associated with a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

Online Product Presentation Formats

Jiang and Benbasat (2007) proposed that rich online presentation formats increase website diagnosticity and buyer's knowledge about products, which in turn impact buyers' intentions to repurchase a product. Jiang and Benbasat (2004) used product diagnosticity to capture a website's ability to convey useful product information and examined the role of various online presentation formats on buyer's product knowledge, showing that both video and virtual product experience lead to higher product diagnosticity than static pictures. Jiang and Benbasat's studies conform with theory of media richness. Three product presentations modes are available in today's online marketplaces – text, pictures, and video (Table 1). Pictures are of particular interest to us since pictures can be categorized as one-dimensional vs. multi-dimensional and real vs. borrowed. One-dimensional pictures are ones that are taken from a single angle, while multi-dimensional pictures are ones that are taken from several different angles. And *real pictures* are ones that are taken by the vendor, *borrowed pictures* are either stock pictures or pictures borrowed from other websites. In contrast, text is of little interest to us since almost all product listings have very similar textual descriptions. Applying the theory of media richness to this context, real pictures provide more accurate information and realistic cues about the authenticity of the product description, while pictures taken from multiple angles provide more detailed profiling about the product's characteristics. Since product presentation formats with higher media richness enhance product diagnosticity, higher product diagnosticity means that buyers can be better informed. Thus they have the potential to reduce product uncertainty. The three product presentation formats reduce description and performance uncertainty as they provide more detailed and credible portraits of products. They reduce fit uncertainty as, the richer the media is, the more interaction with the product buyers feel. Thus, we hypothesize:

H8: Compared with one-dimensional pictures, multi-dimensional pictures reduce a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

H9: Compared with pictures borrowed from other sources, real pictures reduce a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

H10: Video presentation is negatively associated with a) product description uncertainty, b) product performance uncertainty, and c) and product fit uncertainty.

Table 1. Product Presentation Modes in Online Marketplaces that Mitigate Uncertainty

Presentation Mode	Multi-dimensional Pictures	Real Pictures	Video
Description	Pictures taken from multiple angles (versus taken from a single angle)	Pictures taken by the seller (versus borrowed from other sources)	Video

Product Type

Products can be categorized into search and experience goods. According to Nelson (1970; 1974), search goods are those for which users have the ability to obtain information on product quality prior to purchase, while experience goods are products that require sampling or purchase in order to evaluate product quality. Examples of search goods include cameras (Nelson 1970) and supplement pills (Weathers et al. 2007), and examples of experience goods include music (Bhattacharjee et al. 2006; Nelson 1970) and wine (Klein 1998). Although many products involve a mix of search and experience attributes, the categorization of search and experience goods continues to be relevant and widely accepted (Huang et al. 2009). Not every product can be categorized as pure search or experience good, however, products can be described as existing along a continuum from pure search goods to pure experience goods. The difficulty associated with the evaluation of experience products makes buyers feel uncertain about their characteristics and whether the products will meet their needs (Spiekermann et al. 2001). Furthermore, since experience products have more complex characteristics than search goods, buyers are less certain about their characteristics and how those characteristics fit their needs. Thus, we hypothesize:

H11: Experience goods are positively associated with a) product description uncertainty, b) product performance uncertainty, and c) product fit uncertainty.

Research Methodology

Research Context: Taobao.com

Established in 2003 by Alibaba Group, Taobao is the largest online marketplace in Asia. Until 2008, Taobao had more than 100 million registered users and annual transaction value of over 100 billion RMB (about $14.7 billion). According to CNNIC (2008), the total Internet users in China surpassed 360 million by 2009; Taobao's penetration rate is 81.4%, and 67.3% of Chinese online buyers have bought only from TaoBao. Taobao's success, especially its defeat of eBayCN in 2006, made researchers interested in this marketplace (Ou and Davison 2009; Ou et al. 2008). The majority of products on Taobao are new, thus used ones are not studied in this paper. In line with extant research related to experience/ search goods (Huang et al. 2009; Mudambi and Schuff 2010), the products studied in this paper includes typical experience goods such as shoes, clothes, cell phone, camera, furniture, music CD, MP3 player and laser printer. As far as the cultural aspect of the research context is concerned, while the issue is discussed in the concluding remarks, and further research concerning cross-cultural difference is currently in process for a deeper understanding of how different cultures reduce product fit uncertainty, attention focuses here exclusively upon building up the focal construct in this paper.

Interviews, Questionnaire Design and Pilot Study

20 interviews with Taobao buyers were undertaken in September 2009 to acquire a deeper understanding of buyers' uncertainty perceptions and how use of IT artifacts mitigate product uncertainty. The clarity of the questionnaire items was discussed with 20 Taobao buyers and four MIS researchers (two PhD students and two professors). Several variables were modified or discarded. The survey was pretested with 30 Chinese students and pilot tested with 144 Taobao buyers in China. The pilot test showed good measurement and econometric properties. All the survey questions are the same for both the China and US marketplaces respondents.

Follow-up Interviews and Pretests

We set a comment option for the respondents of the pilot study and we did 10 follow-up interviews with the respondents of pilot study. Several insights were drawn for designing a major study. New measurement items were proposed by several respondents in comments and interviews concerning product fit uncertainty, product presentation and product forum. Some control variables, such as offline examine and prior purchase, were also integrated into the main survey. The questionnaire was originally developed in English, then translated into Chinese by two graduate students, who are Chinese and have lived in US for at least 2 years[2].

The survey went through participatory pretesting and undeclared pretest (Converse and Presser 1986) with 50 respondents for each step. The wording of questions in the major survey was refined according to the comments from the participatory pretest respondents and three rounds of discussions between the authors.

Measurement

Dependent Variables

Price premium is not the positive (or negative) premium related to mean price in the overall market, but the positive (or negative) premium related to mean price of the product on Taobao.co, eBay.com and Amazon.com. We believe it is reasonable to use the difference between the product price[3] and average product price on specific marketplace because first, getting the mean product price for a specific product (such as a T-shirt) in the overall market is almost impossible, while on Taobao, eBay and Amazon there are multiple sellers selling the same product

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[2] The questionnaire is translated back into English, and we find the original version is consistent with the translated one.
[3] Shipping cost is not included in the product price.

for each and every category, so for Taobao we averaged the price for the same product (with the same brand, function and conditions) on the first page of a product (about 40 price offers), for eBay we used the same approach, but averaged the "buy-it-now" prices, for Amazon we calculated the mean price for each product as provided in the product page; second, by focusing on the product price in the specific marketplace we don't need to control for the marketplace fixed effects on the product price. Some products are highly unique and do not have multiple sellers, we did not calculate a price premium value for them. The measurement of price premium is in line with extant research such as Dimoka and Pavlou (2008), Rao et al. (1992).

Satisfaction was measured with 9-point Likert Type Scale (Churchill Jr and Surprenant 1982).

Product return was measured as a binary variable (1=returned; 0=did not return).We are concerned that the transaction could have taken place just before the respondents did the survey, and they had not returned product yet, one question is added - "I intend to return the product". We sent follow-up emails on April 15, exactly 14 days after the survey[4]to respondents who intended to return the product, asking whether they actually returned the product. We then updated data on product return.

Repurchase intention was measured with a dummy variable that captured whether the respondent would like to repurchase from the focal seller again in the future if similar products are needed (Ou et al. 2008).

Product Uncertainty Variables

Product description uncertainty and product *performance uncertainty* used measurement items adapted from Dimoka and Pavlou (2008). Items for *product fit uncertainty* went through two rounds of development. We have three items for product fit uncertainty in the pilot study, which showed good reliability (Cronbach's Alpha=0.922). We collected comments from respondents and did follow-up interviews with 10 respondents who offered suggestions about measurement items of this construct, and we thus added two more items, the new measure also showed good statistical properties (see principal component analysis).

Independent Variables

Communication with seller was measured with two variables, first is a dummy variable, capturing whether the respondent contacted the seller prior to purchase, the second is the duration of communication (in minutes), retrieved by the respondent from the IM log file. *Communication with buyers* was measured with a dummy variable, capturing whether the respondent communicated with other buyers prior to purchasing the product. *Use of decision aids* was measured with a dummy variable, capturing whether the respondent visited online decision support websites prior to purchase. *Product forum* was measured with a dummy variable, capturing whether the respondent read posts on Taobao product forum prior to purchase. *Product presentation formats* were measured with five variables. The first was whether the pictures were taken from a single angle or multiple angles (such as up-down, interior, side); the second was whether pictures are taken by the seller, or borrowed from other sources, the third measure was whether there was video of product on the web page, the fourth was to capture many pictures were presented, directly collected from each product web page by an assistant, the fifth was the word count of the presentation, captured with the same method of the fourth variable. *Level of experience of a product* was measured with 7-point Likert type scale. A good is defined as a ''search good'' when full information for dominant product attributes can be known prior to purchase. A good is defined as an ''experience good'' when either condition holds: 1. full information on ''dominant'' attributes cannot be known without direct experience. 2. information search for ''dominant'' attributes is more costly/difficult than direct product experience (Nelson 1974). Prior research on categorization of experience goods and search goods has used "decision time" (Huang et al. 2009; Klein 1998), number of experience attributes (Kim et al. 2009), among others. However, we argue that the whether a product is an experience good and the level of experience is also contingent upon a buyer's perceptions and past experiences with the focal or similar products. Thus we gave instructions and let respondents rate a product's experience level subjectively.

Control Variables

Prior online shopping experience was measured by years of online shopping. *Offline examine* was measured with a dummy variable, capturing whether the respondent examined the product in an offline shop prior to purchase. For *Disposition to uncertainty*, respondents were offered 6 different choices[5] to enter the raffle, similar to the measure design in Frederick (2005). We operationalized their choices into disposition to uncertainty.

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[4]It is the policy of Taobao for buyers to file a return claim within 14 days of product delivery. Besides, for the reader's reference, unlike independent retail websites, Taobao's vendors do not have their own return policies.

[5] 6 choices are: 75% chance of winning 4 RMB; in the same vein, 50%: 6; 25%: 12; 10%: 30; 5%: 60; 2%: 150.

Survey Data

Respondents were Taobao buyers in China. Survey[6] invitations were sent out by a major professional survey company in China, which has a panel pool of 3 million registered member respondents, all of whom are Chinese citizens with Internet experience. Respondents are screened on the first page and only people who currently live in mainland China can proceed with the survey. As suggested by Goetz et al. (1984), to ensure the respondents answer the questions carefully and to secure a decent response rate, we offered incentive of 5RMB (0.8 Dollars) per respondent, plus a random draw of 1 respondent who could win 100RMB ($15), 3 respondents who could win 50RMB ($7.5), 25 respondents who could win 10RMB ($1.5), and 100 respondents who could win 5RMB ($0.8). The incentive was better than the average survey invitations, thus we expected a good quality dataset with less measurement error. Respondents clicked on a hyperlink to the web-based survey instrument. They were informed that the results would be reported in aggregate to ensure their privacy and that they could receive a copy of the study's report.

The survey was live between April 4 and April 9. Overall 2000 survey invitations were sent, 394 respondents entered the survey (19.7% response rate), 50 respondents were screened out because their IP addresses were not from mainland China. In total 344 questionnaires were collected, out of which 28 questionnaires were dropped because respondents claimed not to have purchased products on Taobao in the last month but entered the survey, 32 were deleted because the respondents spent significantly less time as required (as pretested), 25 were deleted for incompleteness, and additional 15 questionnaires were dropped because the manual cross check with website transaction data finds discrepancy between the response and the data on the website. In total 274 valid questionnaires were collected. Respondent's demographics (shown in Table 2) were similar to the professional survey company's panel,[7] and it is also similar to the online shopping demographics in China (CNNIC 2008).

Table 2. Demographic Information of Consumer Sample

Variable	Age	Gender	Education	Experience	Monthly Income
Mean (STD)	25.77 (5.46)	52% Female	82% College	4.58(2.26) years	2783 (3036)

We also set screening questions in the survey to make sure the respondents paid attention when filling out the survey, and we dropped surveys with total response time of less than 5 minutes (participatory pretest show that 90% of the respondents spent more than 7 minutes). For the 43item survey, the respondents spent an average of 18 minutes. We set restrictions to one response per IP address, per computer and per email account.

Transaction Data

We collected the web page the respondent bought the focal product,[8] date of purchase, and the respondents' last four letters/ characters of Taobao ID so we were able to identify each transaction. An assistant was hired to collect information about product presentation formats, and price premium. One of the authors also performed the survey data validation. 15 questionnaires were dropped because a discrepancy was detected between the self-reported data and website data. There was no difference between transaction data and self-reported data in all the remaining questionnaires. Thus, we can safely conclude that all respondents answered questions attentively and correctly. Besides, the transaction date shows that most of our respondents had the Taobao transaction within 10 days (mean=13.07 days, STD=9.81); thus, we trust that the respondents could faithfully recall the focal transaction.

Principal Component Analysis

Principal Component Analysis (PCA) shows that as three dimensions of product uncertainty - description uncertainty, performance uncertainty and fit uncertainty are distinct constructs. All dimensions of product uncertainty and seller uncertainty are distinct constructs, reliability statistics are all above suggested threshold.

Table 3. Principal Component Analysis

	Component 1	Component 2	Component 3	Cronbach's α
DES1	.839	.128	.080	.941
DES2	.883	.240	.133	
DES3	.809	.137	.118	
DES4	.856	.253	.194	

[6] Measurement items can be obtained upon request from the authors, they are omitted for brevity.

[7] Information about the professional survey company and its panel demographics can be obtained upon request from the authors.

[8] Unlike eBay, Taobao's marketplace is not auction type, thus products are listed for a long time. Besides, most of our respondents reported purchase within 10 days of the survey invitation (mean 13.07), the product pages are all still listed.

DES5	.832	.205	.201	
FIT1	.237	.848	.019	.949
FIT2	.274	.864	.156	
FIT3	.194	.893	.142	
FIT4	.187	.909	.132	
FIT5	.146	.886	.124	
PERFORMANCE1	.235	.141	.869	.810
PERFORMANCE2	.178	.169	.888	
Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 5 iterations.				

The Econometric Model

The proposed hypotheses were tested with seven equations which form a two stage regression model. We used Limited Information Maximum Likelihood (LIML) to estimate the equation parameters (Davidson and MacKinnon 1993; Greene 2003; Woodridge 2002). From the first stage, we obtained the value of product uncertainty predicted by the instruments, which was then used to explain outcome variables in the second stage equations.

LIML was used because 1) two of the dependent variables are binary, 2) we aim to use instrumental variables (IV) approach. The LIML method results in consistent and unbiased estimators. The estimators are equal to the 2SLS estimators when an equation is exactly identified (Mariano and Sawa 1972; Rivers and Quang 1988). LIML can be viewed as a least variance ratio estimation or as a maximum likelihood (ML) estimation.[9] LIML is preferred over 2SLS because using least squares method for binary dependent variables will lead to error. Though two dependent variables are continuous, for consistency, we used LIML for the whole system of equations. As a simultaneous equations estimation method, LIML also allows us to account for the endogeneity issue. Thus LIML is also preferred over sequential ML estimation.

The logic behind the IV strategy (Woodridge 2002) is as follows: If we were interested in how IT influences buyers' behavior, our focus would only be on the portion of the variation in the dependent variable that is explained by instruments (IT variables). In general, the instruments in an IV analysis should be correlated with the endogenous variables and should not have a direct impact on the dependent variable.[10] And conceptually a direct association between use of IT artifacts and the four dependent variables cannot be inferred, but the use of IT artifacts is highly correlated with product uncertainty variables, thus we propose the use of IT tools as instruments for the model.

(1) $Price\ Premium = \beta_1 + \beta_1 Description + \beta_1 Performance + \beta_1 Fit + \beta_1 ExperienceGood + \beta_1 SELLER + +\beta_1 Experience + \beta_1 Gender\ + \beta_1 Age + \beta_1 Price + \beta_1 COM1 + \varepsilon_1$

(2) $Satisfaction = \beta_2 + \beta_2 Description + \beta_2 Performance + \beta_2 Fit + \beta_2 ExperienceGood + \beta_2 SELLER + \beta_2 Experience + \beta_2 Gende + \beta_2 Age + \beta_2 Price + \beta_2 COM1 + \varepsilon_2$

(3) $Return = \beta_3 + \beta_3 Description + \beta_3 Performance + \beta_3 Fit + \beta_3 ExperienceGood + \beta_3 SELLER + \beta_3 Experience + \beta_3 Gender + \beta_3 Age + \beta_3 Price + \beta_3 COM1 + \varepsilon_3$

(4) $Repurchase\ = \beta_4 + \beta_4 Description + \beta_4 Fit + \beta_4 Performance + \beta_4 ExperienceGood + \beta_4 SELLER + \beta_4 Experience + \beta_4 Gender + \beta_4 Age + \beta_4 Price + \beta_4 COM1 + \varepsilon_4$

(5) $Description = \beta_5 + \beta_5 SellerOrNot + \beta_5 BuyerOrNot + \beta_5 Forum + \beta_5 DSS + \beta_5 MultiDimension + \beta_5 RealPic + \beta_5 Video + \beta_5 ExperienceGood + \beta_5 Reivew + \beta_5 Disposition + \beta_5 PriorPurchase + \beta_5 OfflineExamine + \beta_5 Experience + \beta_5 Gender + \beta_5 Age + \beta_5 COM1 \quad + \varepsilon_5$

(6) $Performance = \beta_6 + \beta_6 SellerOrNot + \beta_6 BuyerOrNot + \beta_6 Forum + \beta_6 DSS + \beta_6 MultiDimension + \beta_6 RealPic + \beta_6 Video + \beta_6 ExperienceGood + \beta_6 Review + \beta_6 Disposition + \beta_6 PriorPurchasee + \beta_6 OfflineExamine + \beta_6 Experience + \beta_6 Gender + \beta_6 Age + \beta_6 COM1 + \varepsilon_6$

(7) $Fit = \beta_7 + \beta_7 SellerOrNot + \beta_7 BuyerOrNot + \beta_7 Forum + \beta_7 DSS + \beta_7 MultiDimension + \beta_7 RealPic + \beta_7 Video + \beta_7 ExperienceGood + \beta_7 Review + \beta_7 Disposition + \beta_7 PriorPurchase \quad + \beta_7 OfflineExamine + \beta_7 Experience + \beta_7 Gender + \beta_7 Age + \beta_7 COM1 + \varepsilon_7$

Results and Analysis

Linear Relationships

The equations are estimated simultaneously. We used adjusted means for the multi-item variables in the econometric analysis. To parse out common method variance, we included a marker variable.[11]

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[9]The LIML estimator is a K-class estimator with K=k, 2SLS estimator is a K-class estimator with K=1. And OLS estimator is a K-class estimator with K=0.

[10] The Wald test of exogeneity (p<.05) points to the presence of endogeneity, underscoring the need for an IV approach to correct for the specification error.

[11] We estimated the equations with all three marker variables (see Appendix for details), but since all of them were insignificant, we only report one for brevity. Besides, we also included other demographic variables, such as income in our regressions, as since they had an insignificant effect on dependent variables, they were omitted for brevity.

Table 4. Regression Results (N=274)					
	Dependent Variable	**Price Premium**	**Satisfaction**	**Return**	**Repurchase**
	Intercept	7.132 ***	12.889 ***	-0.693 **	1.541 ***
Uncertainty Variables	*Description*	*-1.102*	*-0.093*	*0.033*	*-0.082*
	Performance	*1.548*	*-0.254*	*0.070*	*0.046*
	Fit	**-1.775 +**	**-0.805 *****	**0.055 ***	**-0.087 ****
Control Variables	*Experience Good*	-0.092	0.147	0.026 *	-0.027*
	Seller	-1.264	-0.305	0.046	-0.077
	Online Shopping Experience	0.606	-0.028	-0.027	-0.007
	Gender	-1.730	0.225	0.018	0.021
	Age	0.111	-0.014	-0.001	0.001
	Price	0.031 ***	0.000	0.000	0.000
Marker Variable	*COM1*	-0.506	0.054	-0.012	0.005
	F-value	17.35***	45.45***	18.98***	21.88***
Model Fit	*Adjusted R^2*	.718	.525	.494	.488
Coefficient significant at + .1, * .05, ** .01, *** .001 level					

As the regression results from Table 4 attest, product fit uncertainty was shown to have negative effect on price premium, satisfaction, product returns, and repurchase intention; however, product description uncertainty and performance uncertainty did not have a significant role. Thus, only H1c, H2c, H3c, H4c were supported; in contrast, there was no support for H1a, H1b, H2a, H2b, H3a, H3b, H4a and H4b.

As regression results in Table 5 attest, communication between buyer and seller and communication among buyers had a significant effect on product fit uncertainty, lending support to H5c (weakly supporting H5a and failing to support H5b). Viewing posts on product forums (p<.1) and use of decision support systems (p<.05) both have significant effect in reducing product fit uncertainty, thus H6c and H7c were supported (but there was no support for H6a, H6b, H7a and H7b). Multi-dimensional pictures (p<.001), real pictures (p<.001), video (p<.01) had a significant effect on product description uncertainty, thus supporting H8a, H9a, H10a, respectively. While real picture presentation and video does not reduce fit uncertainty and performance uncertainty (failing to support H9b, H9c, H10b and H10c), multi-dimensional pictures presentation is shown to reduce fit uncertainty (p<.01) and performance uncertainty (p<.05), and H8b and H8c are supported.

Table 5. Regression Results: First Stage (N=274)				
	Dependent Variable	**Fit**	**Description**	**Performance**
	Intercept	8.733 ***	9.923 ***	7.397
Computer Mediated Communication	*Communication with Seller*	-1.724 ***	-0.718 *	-0.613
	Communication with Buyers	-1.499 ***	0.357	-0.046
	Forum	-0.594 +	-0.085	-0.144
Decision Support System	*DSS*	-0.670 *	-0.116	-0.150
Product Presentation Formats	*Multi-dimension Pictures*	-1.011 **	-2.328 ***	-0.823 *
	Real Pictures	0.012	-1.334 ***	-0.470
	Video Presentation	-0.075	-1.563 **	-0.646
Product Type	*Experience Good*	0.126 +	-0.051	-0.079
Control Variables	*Review*	-0.001	-0.007	-0.009
	Disposition	-0.132 +	-0.149 +	0.008
	Prior Purchase	-0.297	-0.186	-0.482 +
	Offline Examine	0.265	0.143	0.055
	Internet Shopping Experience	0.014	-0.068	0.000
	Gender	-0.088	-0.186	-0.184
	Age	-0.015	-0.043	-0.023
Marker Variables	*COM1*	-0.054	-0.057	0.021
	F-value	17.36	17.21	3.63
Model Fit	*Adjusted R^2*	.611	.609	.202
Coefficients significant at + .1, * .05, ** .01, *** .001 level				

There is also evidence that experience goods are associated with product fit uncertainty (p<.05, supporting H11c) but not product description uncertainty or performance uncertainty (fail to support H11a and H11b).

Finally, besides PCA, the fact that description uncertainty, performance uncertainty and fit uncertainty are mitigated by different antecedents further supports their empirical distinction.

In terms of computer mediated communication, both types of online communication had an effect on fit uncertainty. We thus collected data on method of communication. Descriptive statistics (Table 6) reveal that out of the 274 respondents, 234 (more than 85%) used the Taobao IM tool WangWang to communicate with sellers, while 106 (more than 38%) used WangWang to communicate with other buyers. Table 6 also suggests that Taobao's IM tool is widely used by buyers, stressing the importance of online communication for mitigating product fit uncertainty in online marketplaces in China.

Table 6. Descriptive Statistics for Communication Methods in Taobao

Communication	TaobaoWang Wang	Email	Website message system	Telephone	Face to face	Other instant messaging	Did not communicate
With seller	234	0	9	19	0	25	18
Among buyers	106	17	0	0	7	19	159

Non-linear relationships

Beyond the analyses we have conducted above, we proceed to check the non-linearity of several variables, i.e. quadratic forms of *duration of communication with* seller (Min), *number of pictures* (Pics), with product fit uncertainty. The logic and rationale behind the non-linear relationship is both economic and behavioral. Economically speaking, analogous to diminishing marginal utility, the marginal utility (uncertainty mitigation) a buyer gets lowers as more pieces of information are provided, even though sellers incur little marginal cost when providing more information. As far as behavioral explanation goes, for buyers, more communication takes up more "search cost", and more pictures could consume more mental capacity to process information. Thus there might be a threshold that product fit uncertainty cease to drop even duration of communication and number of pictures continue to increase. Through some preliminary analyses such as data plotting, and fitting, we found the actual usage of certain technology and level of fit uncertainty to be non-linearly correlated. We tested non-linearity, specifically focusing on quadratic effects of duration of communication time with seller and number of pictures presented on the product web page with product fit uncertainty.

(8) $Fit = \beta_8 + \beta_8 SellerOrNot + \beta_8 BuyerOrNot + \beta_8 Forum + \beta_8 DSS + \beta_8 MultiDimension + \beta_8 RealPic + \beta_8 Video + \beta_8 ExperienceGood + \beta_8 Review + \beta_8 Disposition + \beta_8 PriorPurchase + \beta_8 OfflineExamine + \beta_8 Experience + \beta_8 Gender + \beta_8 Age + \beta_8 COM1 + \beta_8 Min + \beta_8 Min^2 + \beta_8 Pics + \beta_8 Pics^2 + \varepsilon_8$

(9) d(Fit)/d(Min)=$a1 + 2b1 * Min$

(10) d(Fit)/d(pics)=$a2 + 2b2 * Pics$

From regression analysis we get (a1, b1) and (a2, b2) as estimated parameters (a1, b1, a2, b2 all significant at 0.01 level) of variables *Min* and *Pics*.

First order condition: d(Fit)/d(Min)= -0.034-0.00067*min, s.t. Min $\in (0,80)$, → when d(Fit)/d(Min)=0, Min=50.75 and the shape of the function is concave.

First order condition: d(Fit)/d(Pics)= -0.596-0.032*pics, s.t. Pics $\in (0,25)$, → when d(Fit)/d(Pics)=0, Pics=18.625, and the shape of the function is concave.

Hierarchical Regression

For first stage, we performed hierarchical regression analysis to investigate the impact of duration of communication and number of pictures on product fit uncertainty, and results are presented in the following table.

Table 7. Hierarchical Regressions (N=274)

VARIABLES	Fit (1)	Fit (2)	Fit (3)	Des (1)	Des (2)	Perform (1)	Perform (2)
Communication (Seller)	-1.50***	-1.22***	-0.93***	-0.91***	-0.86**	-0.47	-0.43
Communication (Buyer)	-1.20***	-0.70***	-0.44***	0.1	0.16	-0.35	-0.28
Forum	-0.70***	-0.44***	-0.26*	-0.15	-0.11	-0.12	-0.07
DSS	-0.94***	-0.67***	-0.54***	0.23	0.25	0.02	0.04
Multi-dimension Pics	-0.97***	-0.60***	-0.09	-1.93***	-1.84***	-0.86***	-0.78**
Real Pictures	-0.19	0.20	0.64***	-1.45***	-1.36***	-0.90***	-0.82**
Video	0.10	0.06	-0.07	-1.59***	-1.57***	0.04	0.06
Experience Good	0.13**	0.12**	0.07**	-0.03	-0.04	-0.13**	-0.13**
Disposition	-0.14**	-0.08	-0.07*	-0.09	-0.09	-0.15*	-0.14*
Offline Examine	-0.13	-0.15	-0.19	0.05	0.04	-0.60**	-0.60**
Gender	-0.15	-0.03	-0.13	-0.22	-0.2	-0.347*	-0.32
Min		-0.01***	-0.03***		0		0

Pics		-0.21***	-0.60***		-0.05		-0.04
Min^2			0.0003***		0		0
$Pics^2$			0.02***		0		0
Constant	8.96***	8.07***	8.12***	8.69***	8.52***	8.36***	8.16***
R^2	0.554	0.699	0.807	0.574	0.577	0.318	0.325
R^2 Increase	-	0.145***	0.108***	-	0.004ns	-	0.007ns
*** p<0.01, ** p<0.05, * p<0.1							

As table 7 attests, first, duration of communication with seller and number of pictures both contribute explained variance into the model, increase of R-squared is tested with F statistics. As per the regression results, Model (2) has significant improvement in R-squared over Model (1) (P<0.01). Second, the model for product *fit uncertainty* with non-linear variables (Model 3) makes significant improvement in adjusted has significant improvement in R-squared over both Model (1) and (2) (P<0.01). While product description uncertainty and product performance uncertainty only makes marginal improvement. And although variables Pic, Pic^2, Min and Min^2 are all significant at 0.01 level, number of pictures has a better explanation power over duration of communication, indicating that it is possible in the IM exchanges, buyers and seller not only talk about "product fit" issue, but also other related issues.

To sum up, the above analytical and regression results stand to indicate that there is a threshold at which a consumer feels they have enough product certainty that they'd be willing to make a purchase[12]. And any information beyond that point is useless, which, from our follow-up interview with the respondents, proves to consume buyer's mental capacity to reduce uncertainty in other ways. As we modeled our data as quadratic form, the fitted lines would show increased product fit uncertainty level after the lowest points, however, it is possible that after the optimum level of communication and number of pictures, the line could be a plateau instead of continuously being quadratic. An alternative explanation for the quadratic effects could be too much communication and too many pictures absorbs buyers' mental capacity to discern level of product fit, thus the uncertainty backs up.

Measures to Minimize and Control for Common Method Bias

As this study involves perceptual measures about product uncertainty and satisfaction, it is subjected to common method bias (Malhotra et al. 2006). We tried to minimize common method bias both ex ante and ex post following Podsakoff and Organ (1986) and Podsakoff et al. (2003). Specifically we have undertaken the following measures.

First, common method bias exists if one principal factor counts for the majority of the variance explained (Podsakoff and Organ 1986). The principal components factor analysis (see Table 3) indicates that each principal factor explains roughly equal variance, implying lack of common method bias. Second, the correlation matrix (omitted for brevity) shows that all correlations are below 0.76, while common method bias is often evidenced by extremely high correlations (r>.90) (Bagozzi et al. 1991). Third, we used Lindell and Whitney's (2001) "marker variable" approach with three theoretically unrelated survey items: "how satisfied you are (1) with your work if you are a full-time employee or with your study if you are a full-time student; (2) with your family life; (3) with your experience of using Amazon.cn if applicable." A significant correlation between the survey items and these items could indicate common method bias. However, our tests indicate low correlations (mean |r|=0.034; mean p=0.523), inferring no substantial bias. Fourth, we collected the transaction website URL and seller ID of transactions for each survey respondent, last four letters/characters of their Taobao user ID, the product they purchased and purchase date. Thus, we were able to identify each respondent's transaction, and we crossed checked variables, such as product presentation format and price. The combination of survey and secondary data implies lack of common method bias. These tests show that common method bias does not threaten the study's results. For the sake of precise estimation, we included the marker variables in the model, so that the effects of common method variance could be parsed out.

Robustness Checks

Although LIML does not require stringent assumptions, standard assumptions of maximum likelihood estimation were tested. First, scatter plots of observations and dependent variables do not show any pattern, indicating the independence of observations (i.i.d.). The assumption of normality of errors is not rejected for any of the models at the 5% significance level using the Shapiro-Wilk test (Shapiro and Wilk 1965). Because the LIML procedures that are available do not provide some test statistics, following the method of Brueckner and Largey (2008) we performed more robustness checks in the context of an 2SLS model (linear IV model). First, the 2SLS yields estimations of coefficients with similar level of significance for all predictors. The presence of heteroskedasticity was tested using White's (1980) test, and no evidence of heteroskedasticity was found. The effect of multicollinearity was checked with the variation inflation factors (VIFs) for all the models; the VIFs across all

[12] We thank an ICIS anonymous reviewer for pointing out this potential interesting finding here.

models range from 1.25 to 4.15, suggesting that the estimates obtained are not biased because of multicollinearity (Hair Jr et al. 1995). We did not detect influential observations or outliers for the dataset (all the linear models) using Cook's distance (Cook 1977; Cook and Weisberg 1982) following the guidelines specified by Belsley et al. (1980). For the later part of the data analysis we performed OLS estimation, similar to the above, standard assumptions of OLS are satisfied.

The appropriateness of the instruments was also checked. We conducted statistical tests to confirm the validity and relevance of the instruments. The instruments (use of IT artifacts) were shown to be good predictors in the first stage models (acceptable adjusted R^2 and predictor significance), thus justifying the use of IVs. We also tested that the first-stage F-statistic was highly significant for the model of fit uncertainty and description uncertainty (much higher than the minimum value of 10), alleviating weak instrument concerns (Staiger and Stock 1997; Stock et al. 2002).

Discussion

Key Findings

The results stand to answer the three research questions we proposed. First, product uncertainty is shown to have three distinct dimensions: description, performance, and fit. Second, product uncertainty is associated with negative price premiums, lower satisfaction, more product returns, and lower repurchase intentions. Interestingly, all of these effects are only driven by product fit uncertainty. Fit uncertainty, which is shown to be the most influential dimension of product uncertainty, has seldom been examined before. Thus our results confirm the intuition of many practitioners that product fit is the most important factor in online markets. Third, a set of IT-enabled mechanisms- computer mediated communication, user generated content, decision support systems, and website product presentations - have a significant effect in reducing the three proposed dimensions of product uncertainty.

In conclusion, the difference and relationship between three distinct dimensions can be summarized in the following table.

Implications for Research

Extending the literature on information problems on online marketplaces from seller uncertainty to product uncertainty, this study formally defines and measures *product fit uncertainty*. We developed and validated measurement items for product fit uncertainty in online marketplaces following the rigorous methodology suggested by Churchill (1979), which could serve as a tool for future studies on product uncertainty and related studies of consumer assessment of *fit*. This research model of antecedents and consequence of product uncertainty can be replicated with other data sources and contexts.

Implications for Theory

Drawing on Gregor (2006), we discuss several implications for theory in information systems. From a descriptive stand-point, this paper analyzed and explained consumer’s perception of product uncertainty in online marketplaces. A set of antecedents and consequences of product uncertainty were theorized and tested. Specifically, four IT-enabled uncertainty mitigation mechanisms – CMC, DSS and rich website product presentation formats were theoretically proposed and empirically supported. One of the consequences of product uncertainty - product return has not been inquired by prior research, and is proposed and shown to be associated with product uncertainty. This study explains *why* and *how* use of various IT artifacts can enhance the performance of online marketplaces – by reducing product uncertainty. Furthermore, this study supports and expands Ou et al. (2008)’s explanations for Taobao’s defeat of eBayCN in 2006, as online communication enabled by Taobao’s embedded computer-mediated-communication tools not only build buyer’s trust and guanxi (defined as close and pervasive interpersonal relationships (Ou et al. 2008)) in sellers, but they raise prices for dedicated sellers, increase customer satisfaction, prevent product returns, and enhance repurchases by reducing product fit uncertainty as well.

From a predictive stand-point, this paper shows the importance of reducing product uncertainty to enhance marketplace performance such as reducing product returns. As the research design specifies a time lag between buyers’ *uncertainty perception* and their *product return*, logically causality could be inferred. What’s more, this paper studies a wide array of experience goods and search goods, thus extending prior literature and ensuring the study’s generalizability and enhancing predictability across multiple products so it has better predictive power than existing studies.

From a prescriptive stand-point, this paper offers insights on how to design online marketplaces to improve their effectiveness. As institutional mechanisms for online shopping safety are in place and product presentations become richer and richer with latest technology, product fit uncertainty will increasingly become more influential than seller uncertainty and product description uncertainty, as speculated by several practitioners and empirically confirmed in this study. Accordingly, the design and improvement of online marketplaces should be squarely geared towards reducing product fit uncertainty. As technology and business processes develop in online marketplaces, IT artifacts such as online virtual reality, business processes such as reverse supply chain can be implemented to further reduce product fit uncertainty.

Implications for Practice

First, this study provides a good reference to practitioners as to which aspect of online marketplaces to focus upon to enhance their effectiveness. Second, this study is conducted in the largest online marketplace in China – Taobao, which defeated eBayCN in 2006 and drove it out of the Chinese market. Chinese online marketplaces are developing with a great momentum. As a safe prediction of the former vice president of Microsoft and later former president of Google's Asia Pacific Region business Dr. Kaifu Lee, China's online business will still expand more than 250 times in the next 10 years (Sina.com 2010). Understanding the uncertainty mitigation mechanisms of China's online marketplace Taobao may have important implications for companies that want to expand businesses into China's online market space.

Given that price premium is what differentiates online stores to prevent a market of lemons (Akerlof 1970), customer satisfaction measures the performance of online marketplaces, repurchase intention implies the sustainability of the marketplaces and product returns are costly and contribute to buyer's reluctance to purchase products online, these are important issues online marketplaces and sellers should consider. To ultimately enhance performance, online marketplace intermediaries and sellers should focus on reducing buyer's product uncertainty with emphasis on fit uncertainty with the aid of various IT artifacts.

Concluding Remarks and Suggestions for Future Research

This paper investigates different dimensions of product uncertainty in online marketplaces, their antecedents and consequences. Product fit uncertainty, as the most influential dimension, has not been examined by prior research. This paper makes contribution to the IS literature by conceptualizing product fit uncertainty, theoretically proposing and empirically confirming the role of IT artifacts in reducing product fit uncertainty to avoid lower price premiums, increase buyer satisfaction, reduce cost product returns, and enhance buyers' repurchase intentions.

There are several issues that could limit the results of this study. First, there could be cultural concerns for generalizabiligy of this study. The data of this study is collected in China, which has a different culture from US, and other countries in the world. As far as this study is concerned, technology adoption behavior and uncertainty avoidance are relevant. With different availability of IT artifacts and inclinations, users from different cultural background may employ different CMC tools to reduce uncertainty. Thus, future research could be conducted to examine use of different CMC tools under different cultural backgrounds. And users from different cultures have different uncertainty avoidance levels (Hofstede 1983; Hofstede and Bond 1984), according to Hofstede's UAI, in general people in China (UAI<40) have less uncertainty avoidance than people in US (UAI=46) and the world (UAI=64) (Hofstede 2001), with this in mind, we collected variable "disposition to uncertainty" in the study and aimed to control for this effect.

This study opens several avenues for future research. First, future research could replicate this study by collecting data from other online marketplaces, and to explore additional IT-enabled mechanisms and IT artifacts to reduce product uncertainty, such as liberal product return policies and superior reverse supply chain capabilities that could differently overcome the fundamental problem of product uncertainty. And as technologies advances, future research could include more variables into our models, such as use of virtual reality. Secondly, future research could also make comparisons of product uncertainty in two different marketplaces with different mechanisms, website policies, and cultural backgrounds, e.g., eBay in the United States (risk-neutral culture, has good reputation and credit system) and Taobao in China (risk-averse culture, has less formal credit system and relies more on communication and guanxi for transactions).

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