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The Roles of User Interface Design and Uncertainty Avoidance in B2C Ecommerce Success: Using Evidence from Three National Cultures

ABSTRACT

Most related previous studies have focused on measuring B2C ecommerce success instead of exploring its predictors, and even fewer studies have tested their models across diverse cultures, even though most ecommerce markets involve multiple cultures. Our study extends this line of research by newly identifying and incorporating three predictors of B2C ecommerce success's system-quality dimension: the formatting quality (FQ), picture quality (PQ), and third-party seal (TPS) user-interface-design factors (UIDFs). Given the uncertainty associated with online shopping, we also incorporated uncertainty avoidance's moderating influence on B2C ecommerce success as one of Hoftstede's national culture dimensions. Motivated by cross-cultural research suggesting that behavioral models often do not hold across different cultures, we tested our model using a sample of 768 B2C consumers from Kuwait, Poland, and Latvia. These countries represent three distinct and understudied national cultures: the Arab world, Central Europe, and Eastern Europe. Our results support our newly hypothesized model, suggesting that both picture quality and formatting positively affect system quality, while—surprisingly—TPSs do not. We also found that uncertainty avoidance moderates the relationship between user satisfaction and reuse intentions but not the relationship between perceived value and reuse intentions. Finally, we found that our newly expanded model is robust across the three national cultures we explored; therefore, it can explain reuse intentions in distinct cultures and a B2C ecommerce context. This study's findings present important implications for practitioners and researchers who seek to understand and improve B2C ecommerce success across distinct national cultures.

Keywords: B2C ecommerce success, user interface design, picture quality, formatting quality, third-party seals (TPSs), national culture, uncertainty avoidance, cross-culture.

1. Introduction

The importance of ecommerce success has dramatically increased in the last decade, especially during the Covid-19 pandemic, which accelerated ecommerce use globally. According to the United Nations' Trade and Development experts, the ecommerce sector's retail sales grew from 16% to 19% in 2020, while the top 13 global companies' B2C ecommerce revenues reached 2.9 trillion in 2020 (UN, 2021). A recent report by the Organisation for Economic Co-operation and Development (OECD) demonstrated how Covid-19 accelerated ecommerce's global expansion despite persistent cross-country differences (OECD, 2020). Improving B2C ecommerce success can support business adaptation efforts to meet users' emerging needs and enhance social distancing during the Covid-19 outbreak (OECD, 2020). Given this environment, understanding the explanations for and predictors of B2C ecommerce success across different countries is increasingly important for both researchers and practitioners.

For the last decade, several studies have applied the *DeLone and McLean IS success model* (DeLone & McLean, 1992, 2004), which we refer to hereafter as the *D&M model*, to study B2C ecommerce success in different variations (Brown & Jayakody, 2008; Cenfetelli et al., 2008; Chen & Cheng, 2009; Lai, 2014; Rouibah et al., 2015; Wang, 2008). Although these studies have established a compelling foundation, only a few focused on identifying and studying the predictors of B2C ecommerce success. Identifying and measuring the factors that predict or influence B2C ecommerce success is foundational because developing this knowledge can help researchers and practitioners understand *how* to achieve and enhance this success (DeLone & McLean, 2016). This knowledge can also help managers and practitioners prioritize and direct their investments and design efforts when changing from brick-and-mortar models to ecommerce models or even when improving their existing B2C ecommerce systems. We contribute to this promising research area by introducing three new predictors of B2C ecommerce success's system-quality dimension: the formatting quality (FQ), picture quality (PQ), and third-party seal (TPS) user-interface design factors (UIDFs). From an IS or IT artifact design perspective, this addition plays a particularly crucial role in better explaining why B2C ecommerce consumers are willing to reuse or again transact with an online vendor.

Online shopping involves inherent uncertainty about product features, quality, prices, vendor

credibility, and overall website quality (Karahanna et al., 2013). Given its lack of physical interactions with products and vendors, B2C ecommerce websites' user interfaces are the primary factor that consumers rely on to collect information, develop knowledge, and form initial perceptions of overall website quality and vendor credibility (Karahanna et al., 2013). An ecommerce user interface encompasses the entire user-facing design of a webpage or application, including text, images, videos, visual elements, navigation options, user input options, help features, and more (Lee & Koubek, 2010). B2C user interfaces are not only responsible for facilitating user actions but also for conveying information to consumers and subsequently shaping their overall perception and online experience (Karahanna et al., 2013). B2C ecommerce websites' user interface-design factors heavily influence users' first interactions with these websites; thus, they are crucial in improving quality perceptions and reducing uncertainty (Karahanna et al., 2013; Kuo & Chen, 2011). *Formatting quality* captures design factors related to page color combinations, font colors and sizes, and backgrounds (Kuo & Chen, 2011). Meanwhile, *picture quality* reflects design facets related to websites' visual elements, including pictures' authenticity, resizability, and clarity (Kuo & Chen, 2011). TPSs are another interface-design choice that manifests as visual logos on websites, representing a seal of approval suggesting that these websites' security and privacy policies have been certified by a third-party organization, such as eTrust (Hu et al., 2010; Lowry et al., 2012; Miyazaki & Krishnamurthy, 2002; Rouibah et al., 2016; Yang et al., 2006).

Formatting quality and picture quality are important first to improve websites' usability, a dimension of system quality (Hassan & Li, 2005), and second to signal overall website quality (Mavlanova et al., 2016). TPSs are also key visual design factors of a user interface that assure websites' security and privacy to B2C ecommerce consumers as another dimension of system quality (Rouibah et al., 2015). TPSs also verifiably and expensively signal overall website quality (Mavlanova et al., 2016). Because both usability (Rouibah et al., 2015; Wang, 2008) and security (Rouibah et al., 2015) are key dimensions of system quality, improving these two dimensions by improving formatting quality, picture quality, and TPSs can improve B2C ecommerce websites' perceived system quality. This improvement can, subsequently, improve user satisfaction and lead to repeated B2C website use. Despite the compelling case to consider

how these three constructs (i.e., FQ, PQ, and TPSs) influence B2C ecommerce success, they have been overlooked in previous research. Therefore, we addressed this important gap in the B2C success literature.

National culture is another key factor that can influence how consumers respond to the inherent uncertainty associated with online shopping on B2C ecommerce platforms. This factor remains understudied in the B2C ecommerce literature. Uncertainty avoidance, a dimension of the national culture values by Hoftstede (1980), represents the level of risk that individuals can accept and the extent to which they feel threatened by ambiguous, unstructured, or uncertain situations (Srite & Karahanna, 2006; Yoon, 2009). Customers' decision-making process during online shopping entails substantial uncertainty about several aspects related to products, vendors, and websites (Karahanna et al., 2013). Given this inherent uncertainty, uncertainty avoidance can play an important role in online shoppers' behaviors on B2C ecommerce websites (Yoon, 2009) and, consequently, overall B2C ecommerce success (Karahanna et al., 2013). Despite its prominence, uncertainty avoidance's role in B2C commerce has been inadequately researched, especially in studies involving more than one country. Therefore, we studied uncertainty avoidance's possible moderating influence on the relationships between user satisfaction, perceived value, and reuse intentions.

Finally, most B2C ecommerce success models have been studied in Western contexts, with rare exceptions (Jeyaraj, 2020). Only a few cross-cultural studies have explicitly examined B2C ecommerce success (Karahanna et al., 2013). A recent literature review by Jeyaraj (2020) revealed that, of the 53 key IS success studies, only three were conducted in non-Western contexts. Yet, studies have shown that IS behavioral models frequently do not hold across different cultures (Keil et al., 2000; Lowry et al., 2011; McCoy et al., 2007; Srite & Karahanna, 2006). To address the compelling opportunities presented by these limitations, we tested our newly extended model across three countries: Kuwait, Poland, and Latvia. These countries represent three understudied national cultures (the Arab world, Central Europe, and Eastern Europe, respectively). Testing our model's generalizability across different countries was particularly important, given the recently accelerated global expansion of ecommerce that is forcing ecommerce website designers and practitioners to work across several countries with distinct national cultures.

2. Literature Review and Theoretical Background

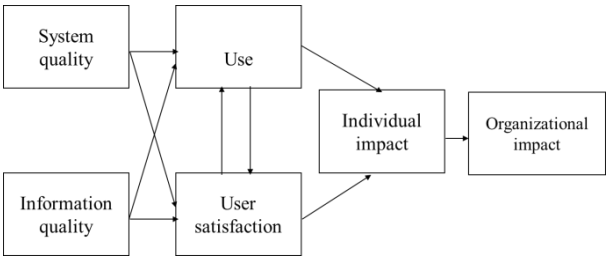
In this section, we discuss the evolution of B2C ecommerce success models over time. Then, we highlight a gap in the literature due to the dearth of studies that have investigated what predicts the system-quality dimension of IS success. Next, we review the IS literature on formatting quality, picture quality, and TPSs to highlight the lack of studies that have investigated these factors' influences on system quality. To theoretically support our hypothesis development, we discuss information asymmetry and signaling in ecommerce, and we explain how website design features (specifically formatting quality, picture quality, and TPSs) can signal quality to buyers and reduce information asymmetry. Finally, we discuss the IS literature on uncertainty avoidance and explain how we contribute to this research stream.

2.1. DeLone and McLean (D&M) IS Success Model and B2C Ecommerce Success

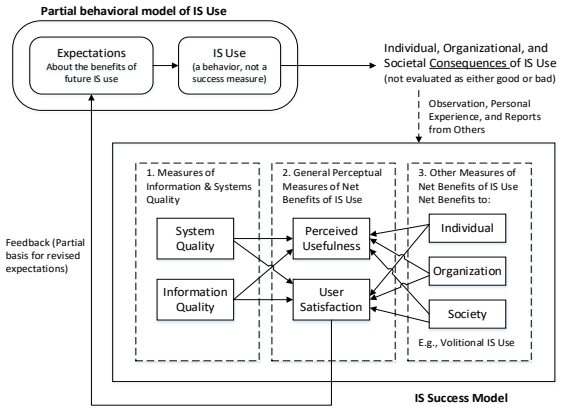
One of the earliest models to measure IS success was developed by DeLone and McLean (1992) **Figure 1.a**). Seddon (1997) shared some of the first criticisms of the original D&M model, claiming that it is confusing because it combines the process and variance factors of IS success. To resolve this confusion, Seddon arranged IS success measures in three columns (**Figure 1.b**). Alongside this improvement, after evaluating the service quality (SERVQUAL) instrument from a marketing and IS perspective, Pitt et al. (1995) suggested that service quality should be added to the model. Further criticism of the original D&M model suggests that limiting IS effects to individuals and organizations is overly simplistic since systems' influences can affect the workgroup level (Ishman, 1996; Myers et al., 1997), interorganizational level (Clemons & Row, 1993), industry level (Clemons et al., 1993), and consumer level (Brynjolfsson, 1996). In response to these criticisms and suggestions, DeLone and McLean (2003) proposed a modified version of their model (**Figure 1.c**).

The growth of ecommerce has created a pressing need to identify new, external measures with which to evaluate customer-facing ecommerce success. After extensively reviewing the ecommerce literature, DeLone and McLean (2004) suggested that the updated D&M success model could still measure ecommerce success, and they further supported this claim with two ecommerce cases. Wang (2008) argued that existing ecommerce success models, including the updated D&M model, faced serious limitations

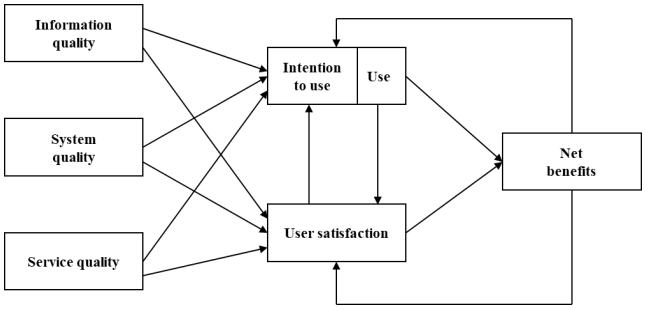
Figure 1. Previous Efforts to Improve the D&M Model



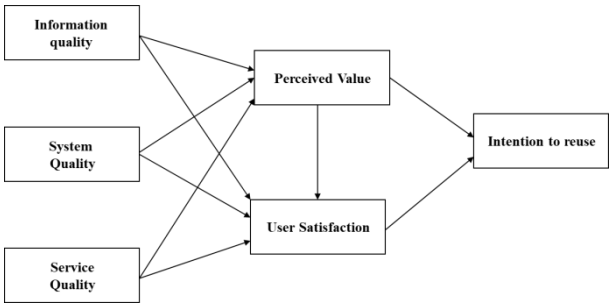
(a) D&M model (1992)



(b) IS Success Model by Seddon (1997, p. 245)



(c) Updated D&M model (2003)



(d) EC System Success Model by Wang (2008)

because both the *use* and *perceived usefulness* constructs were inconsistent with extant ecommerce research. Wang also noted that the *net benefit* construct was too broad to be defined and tested by researchers.

Finally, Wang (2008) explained that the updated D&M model had not been empirically validated in the ecommerce context. Accordingly, Wang (2008) proposed a respecified and validated model of ecommerce success with six dimensions: information quality, system quality, service quality, perceived value, user satisfaction, and reuse intentions. This refined model is depicted in **Figure 1.d**. Moreover, based on empirical testing and validation in an ecommerce context, Wang (2008) suggested that reuse intentions are influenced by user satisfaction and perceived value, which are both affected by service quality, information quality, and system quality. Finally, Rouibah et al. (2015) adopted and expanded Wang's success model to

study B2C ecommerce success in the Arab world after incorporating several enhancements. In this study, we built on the enhanced B2C ecommerce success model by Rouibah et al. (2015).

2.2. System-Quality Dimension of B2C Success

System quality is the dimension of IS success that reflects the desirable aspects of a system (DeLone & McLean, 2016)—that is, in the internet context, an ecommerce website. A review by DeLone and McLean (2016) covered 140 IS success studies and found only three factors that influenced the system-quality dimension of IS success: attitudes toward technology, self-efficacy, and technology experiences. A more recent review by Jeyaraj (2020) on 53 D&M studies between 1992 and 2019 found only three antecedents of system quality: IS knowledge (McGill & Klobas, 2005), trust (Khayun et al., 2012; Teo et al., 2008), and subjective norms (Rana et al., 2015). Despite this interesting analysis, none of these six antecedent factors identified in the reviews concerned IT-artifact or user-interface design, which are crucial to IS and ecommerce research. We responded to this gap in the literature by identifying three user interface-design factors that are crucial to consumers' experiences with B2C ecommerce systems: formatting quality, picture quality, and TPSs. We examined these factors as predictors of system quality.

2.3. Key Factors of Ecommerce Interface Design

2.3.1. Formatting Quality and Picture Quality

Previous studies have used different names and operationalizations to research interface design in relation to formatting B2C websites and their embedded pictures. Eroglu et al. (2001) defined the visual aspects of colors, background patterns, type styles, and fonts as one of three types of computer-mediated atmospheric cues that positively influence online consumers' satisfaction, patronage, purchase amounts, and time spent on shopping websites (Éthier et al., 2008). Van der Heijden (2003) found that perceived attractiveness indirectly influences the actual usage of online shopping websites, while Kim and Stoel (2004) showed that websites' appearances influence customer satisfaction with online retailers. Kumar et al. (2004) demonstrated how colors, as a website interface-design feature, can disrupt websites' ease of use. Later, Cyr et al. (2006) found design aesthetics to indirectly influence loyalty in mobile commerce. Éthier et al. (2008) studied text and visual aspects' influences on overall assessments of online shopping experiences,

including both appraisal and situational states, finding no significant relationship. Meanwhile, Cyr et al. (2010) confirmed that shopping websites' color appeal affects both satisfaction and repurchase intentions. They also confirmed the presence of cultural differences in website design related to color use. Zheng et al. (2019) found that visual appeals increase the likelihood of impulsive m-commerce purchases, while Cheng et al. (2019) showed that color influences trust and arousal among Taiwanese and German consumers. Chopdar and Balakrishnan (2020) found visual attractiveness to positively influence impulsiveness and the perceived value of mobile shopping applications. Finally, a preliminary study by Rouibah and Al-Hasan (2022) showed that interfaces' design aesthetics and picture aspects influence system quality in Kuwait.

Despite previous studies' different terms and operationalizations, formatting and picture quality's influences on predicting B2C ecommerce success have received little research attention. Therefore, we sought to study how these two design factors influence the system-quality dimension of B2C ecommerce success across countries.

2.3.2. Third-Party Seals (TPSs)

TPSs are key user interface-design features that assure B2C ecommerce consumers of visited websites' security and privacy (Hu et al., 2010; Lowry et al., 2012; Miyazaki & Krishnamurthy, 2002; Rouibah et al., 2016; Yang et al., 2006). Previous studies have investigated TPSs' effects on several dimensions of ecommerce adoption but not ecommerce success. Miyazaki and Fernandez (2000) found TPSs to be useful in building trust between customers and online retailers concerning privacy, but not security, concerns. In a follow-up study two years later, Miyazaki and Krishnamurthy (2002) provided evidence that TPSs influence customers' perceived favorableness of websites' privacy practices and policies. Moreover, they found that TPSs can influence information disclosure and website patronage for customers who perceive relatively high levels of online shopping risk but not for low-risk customers. Although Kim et al. (2008) could not establish a significant relationship between TPSs and trust, their findings suggested a negative relationship between TPSs and perceived risk. By contrast, using a sample of B2C ecommerce customers from Kuwait, Rouibah et al. (2016) found that TPSs positively influence both trust and perceived risk among online shoppers. Using a free-simulation online experiment with students from Hong Kong, Lowry

et al. (2012) failed to establish direct significant relationships between perceived privacy assurance and the presence of TPSs, understanding of TPSs, and sense of TPSs' assurance. However, they found evidence that the understanding TPSs and sense of their assurance both moderate the direct relationship between their presence and perceived privacy assurance. A preliminary study by Rouibah and Al-Hasan (2022) showed no relationship between TPSs and perceived system quality in Kuwait. Li et al. (2014) showed that TPSs increase initial trust among Chinese university students who shop online. Finally, Özpolat and Jank (2015) discovered that TPSs are most effective for new shoppers, expensive products, and small online retailers.

Having reviewed the IS literature on TPSs, we conclude first that, despite B2C ecommerce websites' growing use of TPSs, the extant TPSs research has yielded conflicting results on how TPSs influence consumer decision-making (Hu et al., 2010; Lowry et al., 2012; Özpolat & Jank, 2015; Rouibah et al., 2016). Second, no study has explored TPSs' influence on the system-quality dimension of B2C ecommerce success in a cross-country setting. Therefore, we sought to bridge this gap in the literature by exploring how TPSs influence this dimension.

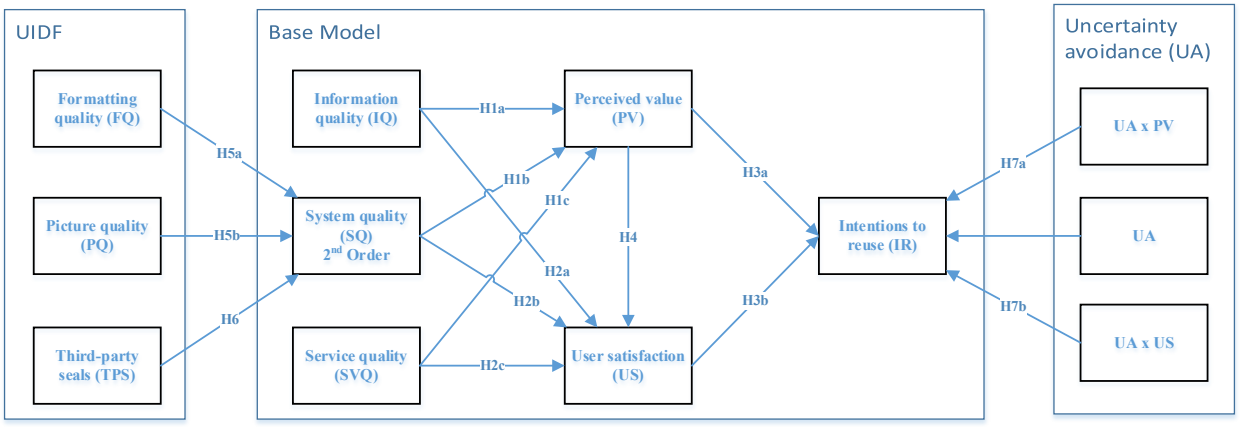
2.4. Uncertainty Avoidance and Ecommerce Success

Uncertainty avoidance is defined as the extent to which an individual can accept risk and feels threatened by ambiguous, unstructured, or uncertain situations (Karahanna et al., 2013; Srite & Karahanna, 2006; Yoon, 2009). Previous research has investigated how uncertainty avoidance influences several aspects of IS, including the adoption of online and mobile commerce (Choi & Geistfeld, 2004; Lim et al., 2004), website design and localization (Callahan, 2005; Cyr et al., 2005; Nitish et al., 2003), perceived website quality and satisfaction (Cyr, 2008; Tsikriktsis, 2002), and trust (Gefen & Heart, 2006; Jin et al., 2008; Yoon, 2009). However, few studies (DeLone & McLean, 1992, 2004; Rouibah et al., 2015; Seddon, 1997; Wang, 2008) have investigated uncertainty avoidance's effect on B2C ecommerce success as specified by IS success models. Of these few studies, the research of Karahanna et al. (2013) most closely resembles our study. They investigated uncertainty avoidance's moderating influence on B2C ecommerce e-loyalty. However, we focused on expanding a B2C ecommerce success model using the collective literature.

3. Research Model and Hypothesis Development

In this section, we develop our theoretical model and operationalized hypotheses for empirical testing. **Figure 2** depicts our final proposed extended research model. Our theorization started with the baseline research model by Wang (2008), enhanced by Rouibah et al. (2015). We explained how information quality, system quality, and service quality jointly influence the mediators of perceived value and user satisfaction

Figure 2. Final Proposed B2C Ecommerce Success Model



and how these factors, in turn, increase reuse intentions. During our second stage of hypothesizing, we expanded the model to the left by adding three system-quality predictors. At the final stage, we expanded the model to the right by incorporating uncertainty avoidance's[1] moderation and direct effects per Hoftstede (1980).

3.1. Confirmatory Hypotheses and Baseline Research Model

In the following subsections, we explain our proposed hypotheses H1–H4 to account for the baseline research model depicted at the center of **Figure 2**.

3.1.1. Perceived Value and the Three Quality Constructs of IS Success

The extant IS success literature concurs that three quality variables must be measured to test IS success: information quality, system quality, and service quality (DeLone & McLean, 2003, 2016; Pitt et al., 1995; Rouibah et al., 2015; Seddon, 1997). *Information quality* is defined as the "desirable characteristics of the system outputs" (e.g., web pages and management reports; (DeLone & McLean, 2016, p. 9). Information quality remains a crucial aspect of B2C ecommerce adoption and continuance even in the platform era

(Jiang et al., 2021; Odusanya et al., 2022). *System quality* is defined as the "desirable characteristics of an information system" (DeLone & McLean, 2016, p. 8). Finally, *service quality* is defined as the "quality of the support that system users receive from IS organization and IT support personnel" (DeLone & McLean, 2016, p. 9). Service quality also remains a critical aspect of user system evaluation in the platform era (Ghavamipoor & Golpayegani, 2020; Moon & Armstrong, 2020; San et al., 2020).

Perceived value is defined as a consumer's overall assessment of the ratio of perceived quality to perceived sacrifice when assessing a product's or service's value (Wang, 2008; Zeithaml, 1988). *Perceived sacrifice* is influenced by both the monetary price and the nonmonetary price, such as time and effort, of a product of service (Rouibah et al., 2015; Wang, 2008; Zeithaml, 1988). Accordingly, perceived value reflects a consumer's perceived monetary and nonmonetary value of a product or service (Rouibah et al., 2015). The predicted relationships among perceived value and information quality, system quality, and service quality have long been established in the literature and are based on the theoretical and empirical work of Rouibah et al. (2015) in the B2C ecommerce context. Accordingly, we replicate the following hypothesis for our cross-cultural B2C ecommerce context:

> **H1.** An increase in (a) *perceived information quality*, (b) *perceived system quality*, and (c) *perceived service quality* increases *perceived value*.

3.1.2. User Satisfaction and the Three Quality Constructs

In the context of B2C ecommerce, *user satisfaction* refers to the degree to which users are pleased with a B2C ecommerce website (Doll et al., 2004; Doll & Torkzadeh, 1991; Rouibah et al., 2015). The hypothesized relationships between user satisfaction and the information quality, system quality, and service quality constructs have also long been established in the literature (DeLone & McLean, 2003, 2004; Seddon, 1997; Wang, 2008) in the context of B2C ecommerce. Accordingly, we replicate the following hypothesis for our cross-cultural B2C ecommerce context:

> **H2.** An increase in (a) *perceived information quality*, (b) *perceived system quality*, and (c) *perceived service quality* increases *user satisfaction*.

3.1.3. Perceived Value, User Satisfaction, and Reuse Intentions

Reuse intentions were introduced by Wang (2008) as an alternative measure of both system usage and net benefits, which were originally suggested by DeLone and McLean (2003). *Reuse intentions* are defined as the "favorable attitude of the customer towards an ecommerce system that results in repeat use/purchase behavior" (Wang, 2008, p. 636). Wang suggested that this measure is conceptually like the customer loyalty construct in marketing and that it can simplify the closed loop between system usage, user satisfaction, and reuse intentions in the ecommerce success context. The hypothesized relationships among the three perceived value, user satisfaction, and reuse intention constructs are established in the literature, based on the theoretical and conceptual work of Wang and recent testing by Rouibah et al. (2015). We thus adopt the following two hypotheses for our context:

H3. An increase in (a) *perceived value* and (b) *user satisfaction* increases reuse intentions.

H4. An increase in *perceived value* increases user satisfaction.

3.2. System-Quality Predictors on a B2C Ecommerce Website

At our next stage of theorizing, we extended the baseline model to the left by adding three predictors of system quality related to interface design: formatting quality, picture quality, and TPSs.[2] In the B2C ecommerce context, a website's user interface is the only channel between sellers and buyers. For online shoppers, the user interface is the most crucial component because it is the only visible part of the B2C system, constituting the window through which shoppers view different capabilities and functionalities (Galitz, 2007). All other components are usually invisible, hidden in code behind the user interface (Galitz, 2007). This interface also presents most system functionalities (Galitz, 2007). Improving interface design through formatting quality, picture quality, and TPSs can improve the perceived overall quality of a B2C website through several mechanisms.

Formatting quality and picture quality are important to improve a website's attractiveness and usability, which are dimensions of system quality (Hassan & Li, 2005). Selecting appropriate fonts, font colors, and background colors is associated with improving website content's readability (Hassan & Li, 2005). The proper use of these elements not only entices users to visit a B2C ecommerce website but can also improve

readability, learnability, and ease of use, which are dimensions of website usability (Hassan & Li, 2005; Rouibah et al., 2015). Moreover, authentic, clear, and resizable pictures can make customers' purchase decisions easier and more effective, allowing them to zoom in and out to observe a product's details. A key consideration is the lack of face-to-face interaction in the ecommerce context; customers cannot physically touch or examine products. Because customers know little about a product, authentic, resizable, and clear pictures can improve and assist their decision-making since pictures enable customers to better judge a product's appearance and quality. Furthermore, formatting (font, color, and background) and pictures are psychologically meaningful and considered important cognitive visual stimuli (Cant & Hefer, 2012). Moreover, formatting quality and picture quality affect a system's attractiveness, especially in the ecommerce environment, because they affect a website's aesthetics (Cyr, 2013; Nathan & Yeow, 2011). As Nathan and Yeow (2011) reported, several studies have concluded that an appealing, attractive user interface significantly increases users' perceived usability of online systems (Brady & Phillips, 2003; Éthier et al., 2008; Lindgaard, 1999; Phillips & Chaparro, 2009). Similarly, Schenkman and Jönsson (2000) concluded that aesthetic appeal is the most significant determinant of website evaluations. A preliminary study by Rouibah and Al-Hasan (2022) showed that website design elements and picture aspects (picture quality) share a positive relationship with perceived system quality.

In addition to improving B2C ecommerce websites' usability and attractiveness, formatting and picture quality can also improve such websites perceived overall quality by signaling quality to users. Among the most crucial characteristics of B2C online markets is the information asymmetry between buyers and sellers, which introduces risk and uncertainty to online purchasing (Mavlanova et al., 2012). Without face-to-face interactions, online buyers have less information to assess the quality of products, sellers, and websites. Signal theory suggests that information asymmetry can be resolved when the more informed party (e.g., ecommerce business) signals quality, revealing private information about unobservable characteristics to the less informed party (e.g., customers) (Leland & Pyle, 1977; Spence, 1973). Formatting quality, picture quality, and TPSs are related to users' first interactions with ecommerce websites. They are important because they signal websites' underlying quality (Mavlanova et al., 2012). This signaling

suggests systems' usability, reliability, stability, and security by demonstrating the quality levels of their design and development, as well as the investment they have received. Thus, these factors signal the high costs and overall quality of B2C websites (Mavlanova et al., 2012).

Moreover, as Booth and Smith (1986) emphasized, certification theory extends signal theory to the context of third-party signal verification (Kleinert et al., 2020). Certifications reveal private information about otherwise hidden attributes and characteristics (Booth & Smith, 1986; King et al., 2005; Kleinert et al., 2020). This reasoning posits that a certificate's value derives primarily from the certificate's ability to convey private information about quality while being easily verifiable. Most B2C consumers are not technically proficient, lacking adequate knowledge to judge the objective, technical security measures on B2C ecommerce websites; therefore, perceived security matters more to consumers than actual security (Kim et al., 2010; Lowry et al., 2012; Rouibah et al., 2016). To improve customers' perceived security and privacy, a dimension of system quality (Kim et al., 2010; Lowry et al., 2012; Rouibah et al., 2016), many B2C websites display TPSs as visual logos on their home or checkout pages to show consumers that they adhere to privacy and security rules and guidance (Kerkhof & van Noort, 2010; Lowry et al., 2012; Rouibah et al., 2016). TPSs aim to assure B2C customers that websites follow and disclose their operating practices and procedures, adhere to security and privacy policies concerning personal data collection, process consumer payments securely and reliably, and clearly express return policies (Kim et al., 2008). Displaying an authentic TPS can send three signals to buyers that address the key criteria of cost and verifiability (Mavlanova et al., 2012). First, acquiring a TPS requires accreditation and compliance with a code of business practices, in addition to paying a membership fee. Second, TPSs are issued by credible, independent organizations that certify the consistency of sellers' behaviors with ecommerce standards. Third, customers can easily verify TPSs' authenticity by checking the websites of certifying third parties. These three signals enhance users' perceived quality of B2C website security, as well as overall website quality.

Given this foundation, we expect formatting quality, picture quality, and TPSs to improve perceived system quality among B2C ecommerce consumers. Therefore, we hypothesize:

H5. An increase in (a) perceived *formatting quality*, (b) perceived *picture quality*, and (c) the *presence of TPSs* increases perceived *system quality*.

3.3. Uncertainty Avoidance's Moderating Role

Finally, we expanded the D&M model to the right by adding the moderation and direct effects of uncertainty avoidance identified by Hoftstede (1980). Uncertainty avoidance can play a key role in consumers' responses to the inherent uncertainty of shopping online (Karahanna et al., 2013) because it represents their levels of acceptable risk and the degrees to which ambiguous, unstructured, or uncertain situations feel threatening (Lowry et al., 2011; Srite & Karahanna, 2006; Yoon, 2009).

Individuals from low-uncertainty-avoidance cultures are more open to change and innovation, whereas individuals from high-uncertainty-avoidance cultures are more conservative, are less open to change, and prefer to work in highly structured, legal, and ordered conditions (Steenkamp et al., 1999; Yoon, 2009). This difference explains why individuals from low-uncertainty-avoidance cultures are more willing to try new products, whereas individuals from high-uncertainty-avoidance cultures are more hesitant to try new products and consequently slower to adopt them (Townsend & Yeniyurt, 2003; Yoon, 2009).

Customers from high-uncertainty-avoidance cultures tend not to switch B2C vendors or complain about their experiences when they are dissatisfied due to the uncertainty inherent to switching costs (Jin et al., 2008; Karahanna et al., 2013; Liu et al., 2001). In contrast, customers from low-uncertainty-avoidance cultures are more likely to switch vendors or complain in this context (Jin et al., 2008; Karahanna et al., 2013; Liu et al., 2001). Therefore, we also posited that uncertainty avoidance positively moderates the relationship between user satisfaction and reuse intentions.

Both higher perceived value and higher user satisfaction may positively influence reuse intentions for B2C ecommerce websites (Rouibah et al., 2015; Wang, 2008). However, these influences are even stronger in high-uncertainty-avoidance cultures because customers from these cultures are less likely to try new things, and they prefer to avoid change and ambiguity. Therefore, they are more likely to continue with an online vendor once they have perceived high value and felt satisfied with their experience. For these customers, this decision entails less hassle than switching to another B2C website, which could present ambiguity. We thus hypothesize:

H6a. *Uncertainty avoidance* positively moderates the relationship between *perceived value* and *reuse intentions* (i.e., the higher the uncertainty avoidance, the stronger the relationship between perceived value and reuse intentions).

H6b. *Uncertainty avoidance* positively moderates the relationship between *user satisfaction* and *reuse intentions* (i.e., the higher the uncertainty avoidance, the stronger the relationship between user satisfaction and reuse intentions).

4. Methodology

Our identification and inclusion of three user interface-design factors (formatting quality, picture quality, and TPSs) were motivated not only by our literature review but also by a preliminary qualitative study to identify which factors affect customers' experiences when shopping on B2C ecommerce online platforms. We briefly describe this qualitative study before detailing our primarily quantitative methodology in the following subsections.

4.1. Preliminary Qualitative Study

Following an approach adopted in prior studies (e.g., Tsohou et al., 2020), we asked 25 university students enrolled in an ecommerce course at a leading business school in Kuwait to reflect on their previous experiences and freely state the key aspects that affected their experiences shopping on B2C ecommerce websites. We collected their answers and applied a format coding procedure to list the factors that may have affected their experiences. In this list, three prominent factors emerged: interface design, including formatting quality; picture quality; and TPSs.

4.2. Primary Quantitative Study

To test our newly expanded D&M model, we designed a survey to collect data from participants in three countries (Kuwait, Latvia, and Poland). After developing and pretesting the survey, we collected data from university students in Kuwait, Poland, and Latvia who were experienced online shoppers. We targeted university students because they represent a vital customer segment for B2C shopping due to their potential as current and future customers (Rouibah et al. (2015). Moreover, university students are considered "digital natives," representing an important online consumer segment of unique users whose consumer behaviors differ from previous generations' (Agárdi & Alt, 2022).

Following Rouibah et al. (2015), we designed the survey to ask each participant to report their most recent B2C ecommerce website transactions. We asked participants to record the name of the last B2C

website from which they had purchased a product or service and to identify the type of product or service they had purchased. Then, we instructed them to complete the survey based on that experience alone. Our data collection in Kuwait leveraged the preliminary study by Rouibah and Al-Hasan (2022), and our data collection in Latvia and Poland followed the same procedures but with respective modifications to produce separate data sets for each country.

All constructs were measured using items adopted from previous studies, some of which were slightly modified to facilitate measurement in our cross-cultural B2C context. Because the original constructs and their measurement items had been published originally in English, and we sought to collect a sample from non-English-speaking participants, we translated and back-translated all the items, following the standard procedures recommended by Lowry et al. (2011). This process aimed to ensure cross-cultural equivalence in the survey items' meanings. Thus, all items were translated from English to Arabic, Polish, and Latvian and back-translated to English. The resulting surveys were then pretested for readability and clarity with samples of 20 undergraduate students from each respective country. During this process, feedback was collected to slightly modify and improve the items' wording of the items. The final survey is presented in Online Appendix A, and item-specific literature documentation is presented in **Table A.1**.

We received a total of 537 responses from students at a major university in Kuwait, 360 from students at a major university in Warsaw, and 91 from students at a major business school in Latvia. Incomplete responses and responses that failed to pass two attention tests included in the survey were excluded. Thus, our final sample comprised 328 valid responses from Kuwait, 330 from Poland, and 80 from Latvia. **Table A.2** in Appendix A presents more details about our final data sample.

5. Analysis and Results

5.1. Pre-Analysis and Validation

To test our path model, we used partial least squares (PLS) regression with SmartPLS, Version 3.2.7 (Ringle et al., 2015). We chose PLS for our analysis because it is especially useful to validate complex models, best supports mixed models with formative and reflective measurements, and is more appropriate than covariance-based structural equation modeling for preliminary model-building (Chin et al., 2003; Gefen et

al., 2011; Lowry & Gaskin, 2014; Lowry et al., 2016; Sarstedt et al., 2016). Moreover, conducting PLS with this software offered the added advantage of reporting model-fit statistics, executing advanced moderation-mediation analysis, and performing robustness checks with multigroup analysis (Ringle et al., 2015).

Following PLS works, we conducted pre-analysis and data validation to establish: (1) the reflective measures' factorial validity through convergent and discriminant validity, (2) a lack of multicollinearity, (3) the formative measure's (i.e., system quality's) validity, (4) the absence of common method bias as a major factor, and (5) strong reliability. See Online Appendix B for all pre-analysis details, including the outer model weights (**Table B.1**), latent variable scores' correlations with indicators (**Table B.2**), collinearity statistics (**Table B.3**), zero-order correlations and interitem correlational diagnostics (**Table B.4**), and measurement model statistics (**Table B.5**).

All reflective latent constructs exhibited high levels of reliability. To establish reliability, PLS computes a composite reliability score as part of its integrated model analysis. This score measures reliability more accurately than Cronbach's alpha because it does not assume that items' loadings or error terms are equal, a flaw of Cronbach's alpha (Chin et al., 2003; Gefen et al., 2011; Lowry & Gaskin, 2014; Lowry et al., 2016). **Table B.6** shows this study's collinearity statistics and reliability. Appendix B further details the study's pre-analyses.

5.2. Analyses of Four Models

In running SmartPLS 3.7.2 for our final analysis, we chose to use the default path weighting scheme with maximum iterations of 300 and a stop criterion of seven. We chose the "mean replacement" algorithm for missing values. The nonparametric bootstrapping procedure was used with 500 subsamples, no sign changes, and bias-corrected and accelerated (BCA) confidential interval calculations. We conducted our analyses hierarchically in four stages so that we could reveal the increased changes in beta coefficients, *t*-statistics, R^2s, and model fit as additional model elements were added. Model 1 represents the core D&M model. Model 2 includes Model 1 with additional system-quality success measures. Model 3 includes Model 2 and culture's direct effects, as well as uncertainty avoidance moderators. Finally, Model 4 includes

Model 3 and the covariate effect on reuse intentions. **Table 1** presents path analysis details, which are summarized in **Figure 3**.

Table 1. Summary of Model Analyses

	Model 1: Base model (Rouibah et al., 2015)		**Model 2: Add FQ, PQ, and TPSs**		**Model 3: Add culture moderation & control**		**Final run: Model 3 + Covariates**	
Tested Path	**β**	***t*-statistic**	**β**	***t*-statistic**	**β**	***t*-statistic**	**β**	***t*-statistic**
H1a. IQ → PV	0.246	5.347***	0.252	5.043***	0.251	4.905***	0.251	5.098***
H1b. SQ →PV	0.286	5.890***	0.284	5.341***	0.284	5.283***	0.284	5.148***
H1c. SQV → PV	0.120	2.925**	0.108	2.501**	0.108	2.503**	0.108	2.640**
H2a. IQ → US	0.177	3.542***	0.188	3.941***	0.188	3.783***	0.188	3.955***
H2b. SQ →US	0.249	4.924***	0.230	4.252***	0.230	4.587***	0.230	4.361***
H2c. SQV → US	0.011	0.306 (n/s)	0.005	0.133 (n/s)	0.005	0.142 (n/s)	0.005	0.137 (n/s)
H3a. PV → IR	0.319	6.495***	0.319	6.537***	0.304	6.695***	0.297	6.431***
H3b. US → IR	0.466	8.596***	0.466	8.827***	0.443	8.455***	0.438	8.079***
H4. PV → US	0.444	11.997***	0.451	12.839***	0.451	12.938***	0.451	12.981***
H5a. FQ → SQ			0.417	11.762***	0.417	12.026***	0.417	11.017***
H5b. PQ → SQ			0.243	6.938***	0.243	6.461***	0.243	6.488***
H5c. TPSs → SQ			0.031	0.945 (n/s)	0.031	0.909 (n/s)	0.031	0.947 (n/s)
Cultural predictions of moderators influencing IR (simultaneous direct effects required to test moderators)								
H6a. (UA x PV) → IR					(-0.059)	1.111 (n/s)	(-0.055)	0.991(n/s)
H6b. (UA x US) → IR					0.130	2.152*	0.101	2.062*
IC → IR (control)					0.027	0.902 (n/s)	0.023	0.742 (n/s)
PD → IR (control)					(-0.041)	1.457 (n/s)	(-0.036)	1.226 (n/s)
UA → IR (control)					0.066	1.948 (n/s)	0.061	1.687 (n/s)
Covariates								
Age							0.020	0.783 (n/s)
Gender							0.014	0.546 (n/s)
Country							(-0.039)	1.006 (n/s)
Education							(-0.008)	0.263 (n/s)
Position							(-0.011)	0.398 (n/s)
Email use							(-0.001)	0.011 (n/s)
Online chat use							0.035	0.993 (n/s)
Search information							0.029	0.605 (n/s)
Online games use							(-0.008)	0.203 (n/s)
Social networking use							(-0.035)	1.229 (n/s)
Frequency of buying							0.071	2.415*
Type purchased product							(-0.042)	1.393 (n/s)
Equation-level and Model Fit Statistics (Based on Estimated Model)								
R^2 (PV)	0.315		0.312		0.312		0.312	
R^2 (US)	0.548		0.542		0.542		0.542	
R^2 (IR)	0.517		0.517		0.530		0.541	
R^2 (SQ)	n/a		0.352		0.352		0.352	
Chi-square	2752.35		4044.51		5482.27		6640.54	
SRMR	0.057		0.052		0.051		0.047	
NFI	0.804		0.784		0.742		0.732	

*** = $p < 0.001$; ** = $p < 0.01$, * = $p < 0.05$, n/s = not significant; FQ = formatting quality; IC = individualism–collectivism; IQ = information quality; IR = intention to reuse; PQ = picture quality; PV = perceived value; PD = power distance; TPSs = third-party seals; SVQ = service quality; SQ = system quality; SQE = SQ: ease of use; SQR = SQ: reliability; SQS = SQ: security; UA = uncertainty avoidance; US = user satisfaction

5.3. Analyses for Multiple Mediation

Our final model proposed two full mediators. It suggested that first, perceived value and, second, user satisfaction fully mediate reuse intentions' direct relationships with information quality, system quality,

and service quality. For mediation, we used the latest bootstrapping method (Hayes, 2009; MacKinnon, 2008), which has been used in IS research to several advantages (Lowry et al., 2016; Vance et al., 2015). It provides greater statistical power, allows for the direct measurement of "indirect effects," and does not assume a normal distribution, unlike the Sobel (1982) method. [3] **Figure 4** depicts the mediation mapping we used for the perceived value and user satisfaction constructs. The bootstrapping mediation results are presented in **Table B.7**. They show that both perceived value and user satisfaction are either partial or full mediators in our model.

Figure 3. Final Model 4 Results without Covariates

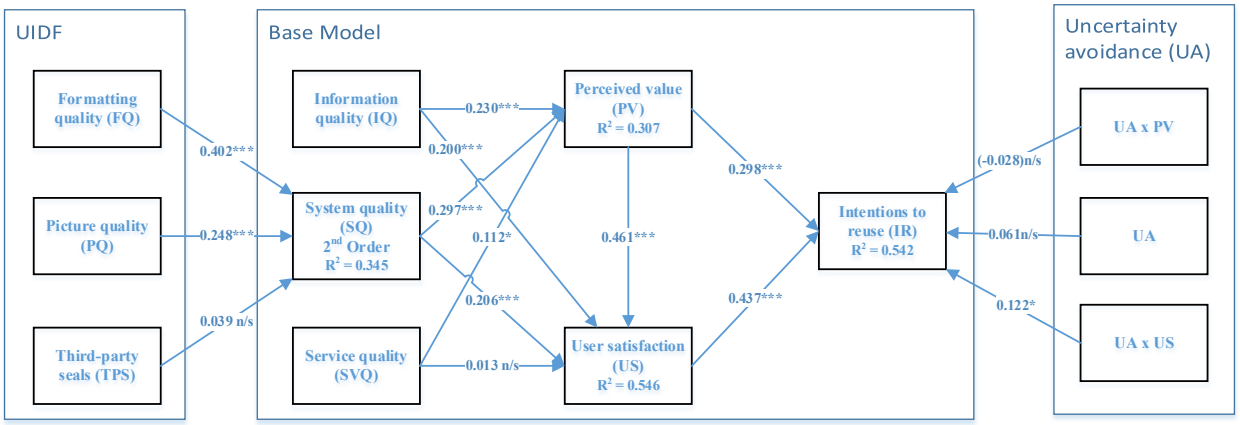
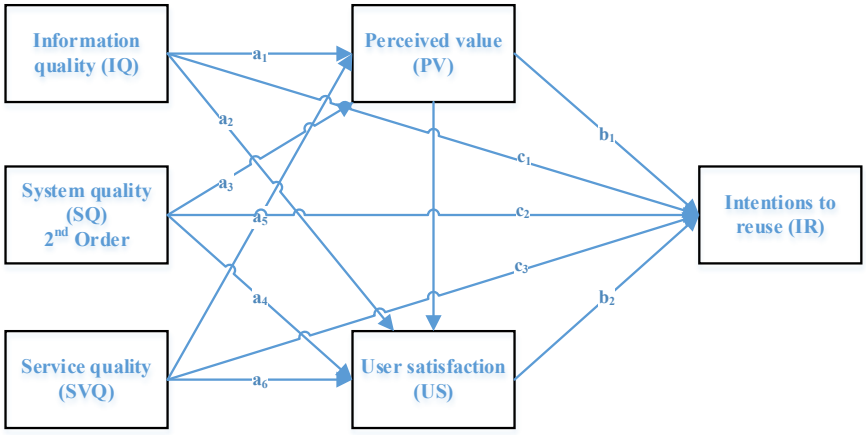


Figure 4. Mediation Mapping to Test Perceived Value and User Satisfaction as Full Mediators



5.4. Robustness Checks with Covariates and Moderators

To test our model's robustness, the first stage was running Model 3 with the moderators and running Model 4 with the covariates (**Table 1**). This process allowed us to check whether other available and known factors

could serve as theoretical counter-explanations to our model. The increase in R^2 and changes in model fit from these additions represented a small but potentially meaningful effect. Notably, in Model 3, uncertainty avoidance's direct effect on reuse intentions was significant, as was the moderation effect of uncertainty avoidance with user satisfaction on reuse intentions. This moderation effect was retained in Model 4, but the direct effect was not. The only significant covariate was the frequency of online purchasing.

5.5. Robustness Checks with Cross-Country Analysis

Because we collected data from three different countries representing three distinct national cultures, we examined our new model's robustness across countries and national cultures. First, we conducted a cross-country comparison to discover any important patterns. For this process, we first split the data set between participants in Kuwait (n = 328), Poland (n = 330), and Latvia (n = 80). We summarized all the latent variables' means by country (see **Table B.8**). Then, we statistically compared them using MANOVA, as summarized in **Table B.9**. The overall MANOVA test was significant at $F = 10.853_{(32, 1310)}$, $p = 0.000$. Many statistically significant differences were observed in the between-subjects effects. Finally, to explore these differences, we ran Tukey's HSD comparisons, as summarized in **Table B.10**.

Second, after establishing the means differences across our sample's three countries, we checked our model's robustness across these countries using the advanced multigroup analysis (MGA) of SmartPLS, Version 3.7.2. This analysis allowed us to test whether predefined country-specific data groups' group-specific parameter estimates—including outer weights, outer loadings, and path coefficients (Ringle et al., 2015)—differed significantly. Thus, we examined whether country-based group distinctions in our data could cause differential or contingent results that might call our model's applicability to certain groups into question or require a more nuanced interpretation for future theory-building.

Our MGA tested the model paths to determine whether differences arose based on participants' countries. MGA only works for pairs, so we applied it to the following pairs: Kuwait versus Poland, Poland versus Latvia, and Kuwait versus Latvia. Interestingly, statistically significant differences were found only for the Kuwait–Poland comparisons and only for two paths. For picture quality → system quality, the β for Kuwait was 0.369, whereas the β for Poland was 0.196 ($p = 0.021$). For formatting quality → system quality,

the β for Kuwait was 0.302, whereas the β for Poland was 0.466 (p = 0.021). No differences were found in any of the other country comparisons.

Thus, our covariate, robustness, and MGA analyses led us to conclude that our full model is highly useful for explaining reuse intentions in three countries: Kuwait, Poland, and Latvia. The model is particularly robust to differences in national origin. (Although MANOVA tests revealed many differences among the latent constructs, the path models were remarkably consistent across countries.)

6. Discussion

Our study's main purpose was to explain how interface design and the national culture dimension of uncertainty avoidance influence B2C ecommerce success and to check our new model's robustness across different national cultures. For this purpose, we built on the ecommerce success model by Wang (2008) and Wang and Liao (2008), which was extended by Rouibah et al. (2015). We added three constructs as predictors of IS success system-quality dimension (i.e., formatting quality, picture quality, and TPSs), and we also added the national cultural dimension of uncertainty avoidance as a moderator of reuse intentions' relationships with user satisfaction and perceived value. To test this model's generalizability, we tested the model with participants from three countries (Kuwait, Poland, and Latvia) representing three distinct national cultures (the Arab world, Central Europe, and Eastern Europe, respectively). Crucially, the model exhibited consistency across these three countries and national cultures. Our findings showed that both formatting quality and picture quality can predict perceived system quality and reuse intentions, whereas TPSs' presence did not exhibit any predictive power in our sample. Also, our findings suggested that uncertainty avoidance moderates the relationship between user satisfaction and reuse intentions but not the relationship between perceived value and reuse intentions. These findings present several interesting implications for both researchers and practitioners, suggesting several future research directions.

6.1. Contributions to Research and Theory

Several studies have used different versions of the D&M model, as well as improvements to the model, to test ecommerce success in various contexts (Brown & Jayakody, 2008; Cenfetelli et al., 2008; Chen & Cheng, 2009; Lai, 2014; Rouibah et al., 2015; Wang, 2008). In reviewing these studies, we identified four

major opportunities that we addressed. First, most of the adopted B2C success models were inconsistent with the ecommerce literature. Wang (2008) addressed these inconsistencies, and Rouibah et al. (2015) later improved upon these solutions. Second, most IS success studies have focused on measuring IS success. Few have focused on identifying the predictors of IS success as a system-quality dimension, and none have done so in an ecommerce context. Third, despite uncertainty avoidance's potential key role in shaping online shoppers' behavior on B2C ecommerce websites, few related studies have considered this factor. Finally, most of the research on B2C ecommerce success models has been conducted in Western contexts, and only a few cross-cultural or cross-country studies have explicitly examined B2C ecommerce success. By addressing these research gaps, our study contributes to the academic literature on B2C ecommerce success in several ways.

*First***,** our study largely built on and extended the B2C ecommerce success model developed by Wang (2008) and further improved upon by Rouibah et al. (2015). These models differ importantly in that Rouibah et al. (2015) found service quality to influence perceived value but not user satisfaction. Those authors suggested that this finding could be due to cultural differences between the participants from Kuwait in their study and the participants from Taiwan in Wang's study. Our findings confirm the results of Rouibah et al. (2015) with participants from Kuwait, Poland, and Latvia. Although we obtained similar results, we can likely rule out their suggestion that power distance (Hoftstede, 1980) may have caused this outcome, because our participants were recruited from three different countries with three different power-distance levels, and we controlled for power distance in our analysis. The power distance scores of Latvia and Taiwan are similar, and both differ considerably from the scores of Kuwait and Poland. Thus, something other than power distance is undermining the link between service quality and satisfaction.

We surmise that this outcome may be related simply to content validity and measurement. By contrast to the study by Wang (2008), most of the measurement items that we used for service quality—which were first introduced by Rouibah et al. (2015)—focused on the mechanical or technical side of service quality (e.g., site intelligence in the form of recommendations, order-tracking, and responsiveness via chat, forums, and emails) than the soft touch or human side (such as face-to-face conversations and social interactions).

Customers in the three countries from which we collected data can generally be described as (1) late ecommerce adopters who are not all fully accustomed to automatic service provisioning, (2) more used to receiving services face-to-face or by telephone communication, and appreciative of transactions' nonmonetary aspects (such as empathy and forms of communication). Notably, we collected data from university students, while the older consumer populations are even more strongly characterized by these cultural inclinations. Such distinctions might suggest a cross-cultural difference between these three countries in that their preferences for service quality may differ from those reflected in the service quality measures. This suggestion calls for further investigation that includes more items into SERVQUAL that address more personal, soft touch, face-to-face, and social elements of service expected in many cultural settings.

*Second***,** in this study, we followed recommendations by Wang (2008) and Éthier et al. (2008) to study factors that influence the system-quality dimension by introducing three predictors related to interface design. Thus, we extend the literature on B2C ecommerce success by improving the explanation of which factors might drive B2C success, especially in the system-quality dimension. Our findings suggest that both formatting quality and picture quality can predict the system-quality dimension of B2C ecommerce success, while TPSs cannot—at least in the three countries where we tested our model. These findings extend the literature's list of potential system-quality antecedents—which includes attitudes toward technology, self-efficacy, technology experience, IS knowledge, trust, and subjective norms (DeLone & McLean, 2016; Jeyaraj, 2020)—to factors that are more related to system design (i.e., formatting quality and picture quality). From an IS or IT artifact design perspective, this addition plays a particularly crucial role in better explaining how B2C ecommerce websites' design may influence online shoppers' perceptions of system quality and, subsequently, their willingness to reuse or again transact with online vendors.

Although formatting quality and picture quality were found to predict system quality, we found no significant relationship between TPSs and perceived system quality despite predicting this relationship. Several reasons could explain this outcome, as other studies have obtained mixed results concerning TPS use and privacy assurance (Lowry et al., 2012; Miyazaki & Krishnamurthy, 2002). Respondents may have

lacked awareness of such seals' meaning, not believed in TPSs' efficacy, or simply distrusted TPSs or similar assurances. We could not determine the precise reason because we controlled for neither consumers' awareness of TPSs' meaning or significance nor their beliefs in TPSs' utility. Accordingly, future research should examine these possibilities—for example, through a study with pre- and post-experimental evaluations.

*Third***,** our research is among the few studies that have investigated how national culture affects B2C ecommerce success by testing the moderating role of the national culture dimension of uncertainty avoidance (Hoftstede, 1980). Perhaps the most relevant study from this stream of research was authored by Karahanna et al. (2013), who investigated uncertainty avoidance's moderating influence on e-loyalty in the B2C ecommerce context. While we joined Karahanna et al. (2013) in furthering the explanation of how uncertainty avoidance affects B2C ecommerce success, our study differs from theirs in several ways. First, though Karahanna et al. (2013) built on a general IS success model that had been developed by Seddon (1997) and amended by Rai et al. (2002), our study built on a more sophisticated model of B2C ecommerce success that had been developed by Wang (2008) and updated and validated by Rouibah et al. (2015) specifically for the B2C ecommerce context. Second, whereas Karahanna et al. (2013) used country-level measures of national culture variables, we measured such variables—including uncertainty avoidance—on the individual level to avoid the ecological fallacy due to individual-level variations in a single country (Srite & Karahanna, 2006). Third, Karahanna et al. studied uncertainty avoidance's moderating influences on perceived usefulness and user satisfaction's relationships with trust, system quality, and information quality, as well as the relationship between website experiences and e-loyalty. Meanwhile, we addressed this gap in their study by testing uncertainty avoidance's moderating influence on reuse intentions' relationships with user satisfaction and perceived value, as well as uncertainty avoidance's direct influence on reuse intentions. Fourth, we avoided the measurement limitations of their study by using a more sophisticated measurement tool previously developed and tested by Rouibah et al. (2015). For example, we used two items to measure user satisfaction instead of the single-item approach used by Karahanna et al. We also used a richer second-order formative construct for system quality with the three first-order

dimensions of ease of use, reliability, and security, instead of the first-order reflective construct that they used. Finally, our study applied more sophisticated statistical methods for our path modeling analysis, multigroup path analysis, mediation analysis, and several other robustness checks, as our analysis section shows (cf §5).

We tested uncertainty avoidance's direct effect on reuse intentions, as well as through the moderating paths of perceived value and the relationship between user satisfaction and reuse intentions. Our findings suggest that uncertainty avoidance only moderates the relationship between user satisfaction and reuse intentions but not the relationship between perceived value and reuse intentions. These findings largely support previous marketing studies suggesting that uncertainty avoidance is the most influential cultural dimension in terms of hindering new product acceptance (Townsend & Yeniyurt, 2003). These findings are also compatible with those of Yoon (2009), who found that uncertainty avoidance is the most influential national culture value that affects customer acceptance and the use of ecommerce. This result is logical because online shopping is often considered risky, with uncertain outcomes that make customers from high-uncertainty-avoidance cultures more reluctant to shop online. These results preliminarily indicate that reducing uncertainty in online B2C transactions might be the most important cultural value for these consumers. If so, factors associated with risk, risk reduction, and privacy issues would be important to these consumers and should be further considered.

Finally, IS success models have been considered mostly in Western contexts, except for rare exceptions (Jeyaraj, 2020). Only a few studies have explicitly examined B2C ecommerce success across different countries or cultures (Karahanna et al., 2013). A recent literature review by Jeyaraj (2020) revealed that, of the 53 key IS success studies, only three were conducted in non-Western contexts. Yet, studies have shown that IS behavioral models frequently do not hold across different cultures (Keil et al., 2000; Lowry et al., 2011; McCoy et al., 2007; Srite & Karahanna, 2006). We bridged this gap in the literature by testing our newly extended model across three countries—Kuwait, Poland, and Latvia, which represent three distinct and understudied national cultures (the Arab world, Central Europe, and Eastern Europe, respectively). Our analyses confirmed that this new model is robust to differences in national culture. Although MANOVA

tests showed several differences among the latent constructs, the path models were remarkably consistent across countries.

6.2. Practical Implications

In addition to its theoretical contributions, this study offers several important practical implications. Identifying and measuring which factors predict IS success can be equally important as, if not more important than, measuring B2C website success per se (DeLone & McLean, 2016). The reason for this importance is that developing knowledge of B2C website success predictors can help both managers and practitioners understand how to achieve B2C website success. Such knowledge can also help them prioritize and direct their investments, as well as their design and marketing efforts (DeLone & McLean, 2016). Our study helps better explain interface-design factors' role in enhancing the system-quality dimension of B2C success and, subsequently, B2C success. It also helps explain the uncertainty avoidance's moderating role on customers' reuse intentions for B2C ecommerce websites. Thus, B2C website designers, managers, and marketers can use our newly extended model to measure, understand, and improve their websites' success. Furthermore, our findings suggest that two key factors should be considered when examining ways to improve reuse intentions for B2C websites.

*First***,** practitioners could focus on improving such websites' formatting and picture quality but not necessarily on acquiring and displaying TPSs. Our findings suggest that improving these quality factors of interface design can improve system quality and, subsequently, perceived value and user satisfaction, which can both increase reuse intentions. To improve formatting quality, practitioners can work on improving page color combinations, font colors, and font sizes. To improve picture quality, they can work on providing clear, authentic, and resizable pictures of the products sold on their websites, helping customers make better decisions when evaluating these products' quality. Interestingly, and conversely to these findings and recommendations, TPSs did not help improve system-quality perceptions for B2C websites in our study. This finding may have resulted from a lack of TPS awareness among consumers, a disbelief in their effectiveness, or apathy toward TPSs. Further research is needed to explain such causes.

*Second***,** we were particularly interested to find that, in our cross-cultural context, uncertainty avoidance

was a key influential moderator of the relationship between user satisfaction and reuse intentions. If this relationship holds elsewhere, B2C website designers, managers, and practitioners in these countries and other countries with high uncertainty avoidance should examine how to reduce consumers' uncertainty and risk perceptions—for example, by improving information quality, system quality, and service quality. More importantly, this positive moderating effect suggests that improved customer satisfaction can be more rewarding in cultures with high uncertainty avoidance than in cultures with low uncertainty avoidance. This finding is particularly important to consider when planning customer satisfaction campaigns in different countries.

6.3. Limitations and Future Research

Although our work offers several contributions to both researchers and practitioners, it also faced several limitations that could be addressed in future research. *First*, our study significantly contributed to the literature as the first research to test the B2C success model specified by Wang (2008) and later improved by Rouibah et al. (2015). However, because we tested the expanded model in Kuwait, Latvia, and Poland, one of our study's limitations is that we did not collect data from Western countries (such as the United States) or Eastern Asian countries (such as Taiwan) to compare our findings with those of Wang (2008). In future research, considering such comparisons would be worthwhile to develop a deeper understanding of how cultural differences affect our model.

Second, our study investigated how the three interface-design factors that we deemed most important (i.e., formatting quality, picture quality, and TPSs) influence the system-quality dimension of B2C success. Although our investigation established a useful foundation for such inquiries, these three factors cannot fully represent the complexity and multidimensionality of user interface design. Future studies could, therefore, benefit from identifying and examining additional features that are pertinent to cross-cultural B2C ecommerce contexts. For example, several B2C ecommerce platforms started providing video files alongside textual descriptions and pictures to help customers assess their products' quality. Accordingly, future studies could investigate video quality's effects on system quality.

Third, our subjects were asked to recall a recent B2C website they had used to conduct ecommerce

transactions and answer survey questions concerning these experiences, but we did not control for the specific time of these transactions, as a controlled experiment would have. Consequently, our data included several periods and was subject to participants' memory and recall. Although our approach is valid and identical to the approaches used in most similar studies previously (Brown & Jayakody, 2008; Chen & Cheng, 2009; Rouibah et al., 2015; Wang, 2008), further methodological approaches are warranted, such as longitudinal studies or classic experiments.

Fourth, similar to the authors of several previous B2C ecommerce studies (Li et al., 2014; Lowry et al., 2012), we collected data from university students who were experienced online shoppers. We targeted university students because they represent a vital customer segment for B2C shopping due to their ongoing and future potential as customers (Rouibah et al., 2015). As we explained in §4.2, these university students are "digital natives" and, thus, an appropriate and crucial online consumer group that should be studied; however, their consumer behaviors differ from previous generations' (Agárdi & Alt, 2022). Therefore, future research should consider other consumer segments—especially consumers who are less educated or older—to obtain richer theoretical insights.

Finally, we did not control some product aspects, such as price and type. Research has suggested that products can be classified by different types, such as convenience, shopping, and specialty goods (i.e., the CSS framework) (Copeland, 1923) or search, experience, and credence products (goods whose qualities cannot be ascertained by consumers even after purchase) (Darby & Karni, 1973; Nelson, 1970, 1974).[4] According to Sheth (1981), customers' preferences and intentions can be affected by: (1) their personal characteristics, demographics, and lifestyles; (2) retailers' types and attributes; and (3) products' types and characteristics (Girard & Dion, 2010). Product types powerfully influence the importance consumers attribute to retailers' attributes (i.e., trust, reputation, brand name, security, perceived value, website quality, information services, and customer services), risk perceptions, and purchases (Girard & Dion, 2010; Lynch et al., 2001). Based on which types of products customers purchase from B2C websites, their perceived value and delayed satisfaction with these websites can differ because quality expectations (i.e., information, systems, and services) can vary by product type. For example, Özpolat and Jank (2015) found that TPSs

appear to be noticed and valued by consumers in contexts involving new shoppers, small online retailers, and expensive products or services. Using the SEC framework to explain differential effects of product types on B2C system success could be an interesting research avenue.

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[1] We tested for Hoftstede's other national culture dimensions and found no significant moderation effect for any except uncertainty avoidance. Also, masculinity–femininity was removed during our factor analysis because of its low factorial validity.

[2] Our identification and inclusion of these three user-interface-design factors (formatting quality, picture quality, and TPSs) were motivated not only by our literature review but also by a preliminary qualitative study to identify which factors influence customers' experiences shopping on B2C ecommerce platforms.

[3] Following Lowry et al. (2016) in testing mediation using bootstrapping with PLS, our mediation testing with bootstrapping essentially complied with the guidelines by Baron and Kenny (1986) for evaluating the three paths in question: (1) from the independent to the mediating variable (*a*), (2) from the mediating to the dependent variable (*b*), and (3) from the independent to the dependent variable (path *c* or *c*′ when considered simultaneously with paths *a* and *b*). However, the key addition of the bootstrap method is that researchers resample (from the obtained sample) with replacements 5,000 times. In each resample, we obtained the product (of *ab*) by multiplying the coefficients in paths *a* and *b*, which estimated the indirect effect in the resample (MacKinnon, 2008). The coefficient corresponding to *c*′ was also obtained. This process should be repeated at least 1,000 times, but preferably 5,000 times, for each of the three paths (Hayes, 2009). Therefore, we used 5,000 resamples. Sorting the values of *ab* and *c*′ in ascending order yields a percentile-based confidence interval, *ci*%. For this purpose, the ordinal positions of *ab* and *c*′ corresponding to the bounds of our interval were calculated using the formula $k(.5 - ci/200)$ for the lower bound and the formula $1 + k(.5 + ci/200)$ for the upper bound (Hayes, 2009). In this case, *k* was the number of resamples mentioned above. We

assumed a standard 95% confidence interval, so our ordinals ranged from 125 (lower bound) to 4,876 (upper bound). Observing the confidence interval *ab*, if we did not find a zero between the upper and lower bounds, we could conclude with confidence of *ci*% that the indirect effect existed (MacKinnon, 2008). Examining the confidence interval for *c′* allowed us to infer whether the mediation was full or partial. If *ab* is nonzero and *c′* is zero, full mediation is indicated; conversely, if both *ab* and *c′* are nonzero, then partial mediation can be inferred.

[4] *Search products* are products whose attribute information (e.g., price, quality, performance, dimension, size, color, style, safety, and warranty) can be obtained easily before purchasing or using the products. *Experience* products are products whose attribute information cannot be obtained until the products are purchased or used. *Credence* products are products whose attribute information is not available before or after the products' use for a considerable period (Darby & Karni, 1973; Girard & Dion, 2010; Nelson, 1970, 1974).

Online Appendix A. Survey and Measurement Details

Gender:

- Male
- Female

What is your age?

Which best describes you?

- Employee
- Student
- Not employee

Education Level:

- High school & lower
- Diploma degree
- Bachelor's degree
- Master's degree
- Ph.D. Degree

I use the Internet to do the following (you can choose more than one):

- E-mail
- Online shopping
- Online chat
- Search information
- Online games
- Social networks/ blogs
- Other (please describe):

I buy things online:

- Once a year
- 2 to 4 times a year
- 5 to 10 times a year
- More than 10 times a year

What is the last online shop you have purchased from?

What was the product or service you purchased from that website?

- Clothing
- Accessories / bags / watches
- Software
- Electronics / computers
- Music / Videos
- Books/eBooks / Magazines / Newspapers
- Travel (airline tickets / hotel booking)
- Sport equipment
- Order restaurants
- Other (please describe):

How many times did you use this website for purchases?

Please provide your evaluation to the following statements regarding the last website you have bought from on the following scale: 1 = Strongly disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly agree

Table A.1. Measurement Details

Latent Constructs	Prompts and Items	Measurement source
Information quality (IQ)	IQ1. The website provides the precise information that I need.	Doll and Torkzadeh (1988) and Rouibah et al. (2015)
	IQ2. The information content of the website meets my needs.	
	IQ3. The website provides sufficient information.	
	IQ4. The website provides accurate information.	
	IQ5. The information is presented in a useful format.	
	IQ6. The information on the website is clear.	
	IQ7. The website provides up-to-date information.	
	IQ8. The website shows complete information of products.	Kuo and Chen (2011)
	IQ9. All processes (shopping, paying and support) on the website are explained clearly.	
	IQ10. The website shows evaluation information of product (e.g., ratings, reviews).	
SQ ease of use (SQE)	SQE1. The website is user friendly.	Same sources as IQ1–7
	SQE2. The website experiences an easy-to-use shopping cart.	Kuo and Chen (2011)
	SQE3. The website shows purchase history in my account.	
	SQE4. The website offers flexible alternative payment methods (e.g., check, credit card, PayPal).	
	SQE5. The website shows multi-dimensioned categorized products (e.g., by brands, price range	
	SQE6. The website offers the ability to compare products with similar ones.	
	SQE7. The website provides bookmarks of products viewed.	
	SQE8. The website is easy to use.	Same sources as IQ1–7
SQ reliability (SQR)	SQR1. The website is always up and available.	Rouibah et al. (2015)
	SQR2. The website is NOT subject to frequent problems and crashes.	
	SQR3. The website provides well-built advanced search engine.	Kuo and Chen (2011)
	SQR4. The search engine provides accurate keyword search ability.	
SQ security (SQS)	SQ5. On the website there is opportunity to create individual account with logon-id and password.	Rouibah et al. (2015)
	SQ6. The website ensures transactions security.	
	SQ7. The website protects consumers' privacy.	
	SQ8. Payment is made through secure payment gateways.	Kuo and Chen (2011)
Service quality (SVQ)	SVQ1. The website provides recommendations of products/services according to customers' preferences.	Rouibah et al. (2015)
	SVQ2. Order tracking service is available until delivery.	
	SVQ3. When I have a problem, the website provides online support sources (e.g., email, chat room, forum, FAQ).	
	SVQ4. The website provides exchange and clear refund policies.	Kuo and Chen (2011)
	SVQ5. The website provides warranty and maintenance for purchased products.	
	SVQ6. The website assures delivery through well-known delivery companies (e.g., DHL, Aramex).	
	SVQ7. The web site provides high prompt support service.	Gorla et al. (2010)
	SVQ8. The web site provides high reliable support service.	
	SVQ9. The web site provides high responsive support service.	

Latent Constructs	Prompts and Items	Measurement source
Perceived value (PV)	PV1. Shopping on this website is very good deal.	Rouibah et al. (2015)
	PV2. The effort I put in to shop on this website is very worthwhile.	
	PV3. Shopping on this website saves my time.	
	PV4. Overall, the use of the website would deliver me good value.	
User satisfaction (US)	US1. Overall, I was satisfied with this online purchasing experience.	Rouibah et al. (2015)
	US2. It was possible for me to buy the product/service of my choice easily.	
Intention to reuse (IR)	IR1. Assuming that I have access to the website, I intend to reuse it.	Rouibah et al. (2015)
	IR2. I will reuse the website in the future.	
	IR3. I will frequently use the website in the future.	
Formatting quality (FQ)	FQ1. Font sizes of the website are effectively used to distinguish between title and content.	Kuo and Chen (2011)
	FQ2. Font color of the website is effectively used to distinguish between information displayed.	
	FQ3. The combinations of colors used in the webpages are well selected (e.g., Background).	
Picture quality (PQ)	PQ1. The website provides authentic and real pictures of products.	Kuo and Chen (2011)
	PQ2. Pictures of products are provided in different sizes.	
	PQ3. The website shows high quality and clear pictures.	
Third-party seals (TPSs)	TPS1. I prefer to buy from websites that carry "third-party seal".	Rouibah et al. (2016)
	TPS2. Third-party seals make me feel more comfortable to buy from the website.	
	TPS3. Third-party seals make me feel more secure in terms of privacy.	
	TPS4. Third-party seals make me feel safer in terms of the transaction.	
Individualism–collectivism (IC)	IC1. Group welfare is more important than individual rewards.	Dorfman and Howell (1988)
	IC2. Group success is more important than individual success.	
	IC3. Being accepted by the members of your group is very important.	
Uncertainty avoidance (UA)	UA1. It is important to have requirements and instructions spelled out in detail so that you always know what you are expected to do.	Dorfman and Howell (1988)
	UA2. Rules and regulations are important because they inform you what is expected of you.	
	UA3. Standard procedures and policies are helpful to people.	
Masculinity–femininity (MF)	MF1. Men usually solve problems with logical analysis; women usually solve problems with intuition.	Dorfman and Howell (1988)
	MF2. Solving problems usually requires direct approach, which is typical of men.	
	MF3. It is better to have a man in a high-level position rather than a woman.	
Power distance (PD)	PD1. It is frequently necessary for a superior to use authority and power when dealing with their subordinates.	Dorfman and Howell (1988)
	PD2. Superiors should seldom ask for the opinions of their subordinates.	
	PD3. Subordinates should not disagree with their superior’s decisions.	

Notes: System quality (SQ) is a second-order formative construct made of SQE, SQR, and SQS.

Table A.2. Descriptive Participants by Country (n = 738)

	Kuwait		Poland		Latvia	
Responses	537		360		91	
Valid Responses	328		330		80	
Gender	n	%	n	%	n	%
Male	95	29.0	146	44.2	45	56.3
Female	233	71.0	184	55.8	35	43.7
Total	328	100.0	330	100	80	100
Age						
Less than 20 years	87	27	5	1.5	8	10
21–30 years	156	48	310	93.9	62	77.4
31–40 years	55	17	12	3.6	9	11.3
More than 40 years	30	9	3	.9	1	1.3
Total	328	100	330	100.0	80	100
Education Level						
High school & lower	40	12.2	0	0	49	61.25
Diploma degree (2 years university degree)	10	3.0	236	71.5	14	17.5
Bachelor's degree	210	64.0	63	19.1	15	18.75
Master's degree	54	16.5	31	9.4	0	0
Ph.D. Degree	14	4.3	0	0	2	2.5
Total	328	100.0	330	100	80	100
Internet activities						
Send & receive emails	301	91.8	307	93.0	76	95
Chatting	148	45.1	299	90.6	47	58.8
Searching for information on the web	300	91.5	314	95.15	71	88.8
Play online games	87	26.5	109	33.03	19	23.8
Blogging & participating in social networks	260	79.3	293	88.79	67	83.8
Frequency online purchasing						
Once a year	63	19.2	22	6.7	15	18.8
2–4 times a year	105	32	79	23.9	23	28.8
5-10 times a year	84	25.6	98	29.7	21	26.3
> 10 times a year	73	22.3	131	39.7	20	25.0
Missing	3	0.9	0	0.0	1	1.3
Total	328	100	330	100.0	80	100.0

ONLINE APPENDIX B. Factorial Validity and Analysis Supplement

Formative or Reflective Constructs?

A key step in preparing to assessing factorial validity is to determine which constructs are formative and which are reflective (Diamantopoulos & Winklhofer, 2001).[i] We followed Cenfetelli and Bassellier (2009) as the basis for determining which constructs were formative and which were reflective. In this assessment, the most important consideration is to see how the constructs were theoretically formed and validated in other literature, to make sure no contradictions exist in their current use, and to model the constructs consistently. All of our measures were considered reflective with one key exception: system quality, which according to the literature we borrowed it from was a second-order formative measure formed by three first-order reflective constructs: perceived ease of use, system reliability, and system security (e.g., Doll & Torkzadeh, 1988). We validated and modeled all constructs, accordingly.

Factorial Validity for the Reflective Constructs

Factorial validity of reflective constructs is established by establishing both convergent validity and discriminant validity, two highly interrelated concepts that must coexist. Importantly, factorial validity is established in diverse ways for reflective and formative constructs; thus, we discuss these analyses separately.

To establish the factorial validity of our reflective constructs, we followed procedures shown by Gefen and Straub (2005) and Lowry and Gaskin (2014). For an especially conservative analysis, we used two established techniques to establish convergent validity and two established techniques to establish discriminant validity. First, we examined the outer model loadings, summarized in Table B.1. Following Gefen and Straub (2005), convergent validity can be established when the t-values of the outer model loadings are significant. All items in the model passed these checks. Moreover, all loadings were above the conservative 0.500 threshold.

As a second check, we correlated the latent variable scores against the indicators as a form of factor loadings and then examined the indicator loadings and cross-loadings to establish convergent validity (see Table B.2). Although this approach is typically used to establish discriminant validity (Gefen & Straub, 2005), convergent validity and discriminant validity are interdependent and help establish each other (Straub et al., 2004). Thus, convergent validity is also established when each loading for a latent variable is higher than those for other latent variables.

We also used two approaches to establish discriminant validity, as described by Gefen and Straub (2005) and Lowry and Gaskin (2014). First, as with convergent validity, we examined the factor loadings, but this time to ensure significant overlap did not exist between the constructs. To be extra conservative, and since we had more reflective items than was minimally needed, we dropped any items that had cross-loadings below 0.600. Second, we used the approach of examining the square roots of the AVEs described by Fornell and Larcker (1981) and Staples et al. (1999)[ii] Strong discriminant validity was shown for all subconstructs, using both approaches. All the AVE thresholds were exceeded for all latent constructs, as summarized in Table 1, which also displays the measurement model statistics for all first-order reflective constructs.

Mono-Method Bias

Several steps were taken a priori to decrease the likelihood of common-method bias from occurring in our data collection, as discussed in the main text. However, all data was collected using a similar-looking online survey; thus, we tested for common-method bias to establish that it was not a likely negative factor in the data remaining for our analysis.

The most important problem of common-method bias is that it causes the constructs of a model to be highly correlated with each other. Thus, our main approach was simply to examine a correlation matrix of the constructs and to determine if any of the correlations were above 0.90, which is evidence that common-method bias may exist (Pavlou et al., 2007). These correlations—all of which were significantly below the

0.90 threshold—are presented in the measurement model statistics in Table 1.

In addition, we had gathered a marker variable, masculinity-femininity, which we could use to further establish that common-method bias exists. A marker variable is one that is prone to social desirability bias (i.e., people are likely to respond highly in the affirmative) and that is unrelated to the theoretical model being tested. We had originally hoped to gather this variable for our model, but we encountered problems with its cross-cultural equivalence and social desirability; thus, we decided it would be an ideal marker variable. The idea here is that if common-method bias existed, then all (or most) constructs would be highly correlated, including the marker variable. The simplest way to test this was to run the marker variable in the correlation matrix of all variables. We did so against all the major constructs of our model and found exceptionally low correlations (see Table 1). This provides further evidence that common-method bias is not a legitimate threat to this study.

Checking for Multicollinearity

Another key threat to check for with SEM is the potential threat of multicollinearity, and thus we followed the latest standards in checking for multicollinearity with all construct items. VIFs less than 10 are traditionally viewed as justification for a model's lack of multicollinearity, with 5.0 being ideal; however, if the items are involved in a formative construct, the ideal level should be below 3.3 (Cenfetelli & Bassellier, 2009). All the first-order reflective constructs had variance inflation factors (VIFs) for outer VIFs well below the conservative threshold of 5.0 and thus involved in formative constructs (i.e., system quality items) were all below the conservative threshold of 5.0 (Table B.3). This trend held for the inner VIFs (Table 2), with the exception that one reflective construct was slightly above 5.0. However, overall, there is little indication multicollinearity is a threat to the model.

Reliabilities

As a product of our rigorous pre-analysis, all our reflective subconstructs exhibited high levels of reliability. To establish reliability, PLS computes a composite reliability score as part of its integrated model analysis. This score is a more accurate measurement of reliability than Cronbach's alpha because it does not assume that loadings or error terms of the items are equal. However, we also included Cronbach's alpha as a conservative check, and all these values were above the minimum threshold of 0.700, except for customer lock in, but its composite reliability was good. These values are summarized in Table 2 and indicate strong reliabilities.

Factorial Validity of Formative Constructs

Again, system quality (SQ) is a second-order formative construct composed of first-order reflective subconstructs (SQ reliability, SQ ease of use, SQ security), and all have been theoretically and empirically validated in the previous literature (Doll & Torkzadeh, 1988; Rouibah et al., 2015). Here, we further rigorously establish validity of these constructs to improve our analysis. Establishing factorial validity for formative indicators is more challenging than validating reflective indicators, because the established procedures that exist to determine the validity of reflective measures do not apply to formative measures (Petter et al., 2007; Straub et al., 2004), and the procedures for validating formative measures are less known and established (Diamantopoulos & Winklhofer, 2001) although standards are beginning to emerge (Cenfetelli & Bassellier, 2009).[iii] We use these latest standards published by Cenfetelli and Bassellier (2009). However, the biggest potential issue that must be addressed is multicollinearity (Cenfetelli & Bassellier, 2009), which we have already addressed.

As the next step for validating our second-order formative construct, we first assessed the absolute indicator contributions (i.e., zero-order correlations) of its individual items against the overall second-order average. The goal in this step is to improve internal validity by removing items not exhibiting a significant association with the overall construct (Cenfetelli & Bassellier, 2009; Diamantopoulos & Winklhofer, 2001).[iv] All of the items showed significant associations with the overall measure at the 0.05 level of significance, and thus none of these items were removed during this step.

As part of this analysis, we also performed inter-item correlational diagnostics to assess if there were unusually high correlations amongst the formative indicators, as these can significantly weaken formative measures (Diamantopoulos & Siguaw, 2006). As expected, all the system quality items were correlated (except two, which can happen with formatives), but all were well below a high correlation threshold of 0.900. These statistics are summarized in Table B.4.

Summary of Pre-Analysis Validation

Our pre-analyses show that our data exhibit strong factorial validity of the reflective constructs, little multicollinearity, strong reliability, and that they lack mono-method bias. In summary, the results of our validation procedures show that our model data meets or exceeds the rigorous validation standards expected in modern research (Straub et al., 2004)—particularly for PLS analysis for reflective constructs (Gefen & Straub, 2005) and formative constructs (Cenfetelli & Bassellier, 2009; Diamantopoulos & Siguaw, 2006; Petter et al., 2007).

Table B.1. Outer Model Weights to Establish Convergent Validity

Latent construct	Items	Loading	*t*-statistic	*p*-value
Individualism–collectivism (IC)	IC1	0.672	7.855	0.000
	IC2	0.705	8.764	0.000
	IC3	0.843	14.223	0.000
Information quality (IQ)	IQ1	0.813	49.869	0.000
	IQ2	0.805	44.543	0.000
	IQ3	0.825	47.840	0.000
	IQ4	0.760	34.322	0.000
	IQ5	0.747	32.667	0.000
	IQ6	0.769	32.695	0.000
	IQ7	0.326 (d)	1.740	0.082
	IQ8	0.713	30.263	0.000
	IQ9	0.644	23.756	0.000
	IQ10	0.193 (d)	2.037	0.042
Intentions to reuse (IR)	IR1	0.891	59.575	0.000
	IR2	0.895	80.042	0.000
	IR3	0.830	47.395	0.000
Picture quality (PQ)	PQ1	0.824	38.055	0.000
	PQ2	0.699	19.016	0.000
	PQ3	0.871	59.525	0.000
Power distance (PD)	PD1	0.511 (d)	2.883	0.004
	PD2	0.616	3.745	0.000
	PD3	0.944	6.867	0.000
Perceived value (PV)	PV1	0.815	51.165	0.000
	PV2	0.522 (d)	2.448	0.015
	PV3	0.812	42.414	0.000
	PV4	0.798	31.940	0.000
System quality ease-of-use (SQE)	SQE1	0.668	17.064	0.000
	SQE2	0.728	24.558	0.000
	SQE3	0.634	15.877	0.000
	SQE4	0.594 (d)	14.798	0.000
	SQE5	0.706	23.829	0.000
	SQE6	0.328 (d)	5.647	0.000
	SQE7	0.484 (d)	9.180	0.000
	SQE8	0.367 (d)	1.604	0.109
System quality reliability (SQR)	SQR1	0.725	22.333	0.000
	SQR2	0.738	25.677	0.000

Latent construct	Items	Loading	*t*-statistic	*p*-value
	SQR3	0.722	22.148	0.000
	SQR4	0.728	22.919	0.000
System quality security (SQS)	SQS1	0.318 (d)	1.501	0.134
	SQS2	0.895	44.750	0.000
	SQS3	0.865	34.419	0.000
	SQS4	0.255 (d)	1.530	0.127
Service quality (SVQ)	SVQ1	0.448	10.571	0.000
	SVQ2	0.587 (d)	16.445	0.000
	SVQ3	0.675	22.788	0.000
	SVQ4	0.638	21.489	0.000
	SVQ5	0.261 (d)	1.749	0.081
	SVQ6	0.522 (d)	13.425	0.000
	SVQ7	0.823	51.119	0.000
	SVQ8	0.801	42.782	0.000
	SVQ9	0.812	42.966	0.000
Third-party seals (TPSs)	TPS1	0.609	3.437	0.001
	TPS2	0.905	90.953	0.000
	TPS3	0.909	61.106	0.000
	TPS4	0.916	71.446	0.000
Uncertainty avoidance (UA)	UA1	0.830	42.983	0.000
	UA2	0.851	43.394	0.000
	UA3	0.821	38.085	0.000
Formatting quality (FQ)	FQ1	0.836	43.989	0.000
	FQ2	0.839	39.382	0.000
	FQ3	0.827	44.895	0.000
User satisfaction (US)	US1	0.918	116.427	0.000
	US2	0.908	87.611	0.000

Notes: All items' loadings were significant, except for three; however, to be conservative and since we had plenty of reflective items, we also dropped any items that were below the threshold of 0.600, as denoted by "(d")

Table B.2. Correlations of Latent Variable Scores against the Indicators to Establish Convergent and Discriminant Validity)

Items	IC	IQ	IR	PQ	PD	PV	SQE	SQR	SQS	SVQ	TPS	UA	FQ	US
IC1	.672	.059	.093	.206	.205	.181	.072	.081	.090	.108	.236	.217	.131	.090
IC2	.705	.113	.104	.164	.217	.165	.066	.091	.064	.141	.271	.245	.133	.102
IC3	.843	.168	.208	.177	.049	.197	.135	.095	.126	.130	.232	.462	.217	.204
IQ1	.150	.814	.445	.359	-.100	.395	.461	.428	.397	.394	.194	.268	.372	.480
IQ2	.137	.806	.390	.332	-.110	.354	.436	.407	.401	.366	.147	.250	.368	.432
IQ3	.133	.826	.411	.382	-.130	.385	.442	.383	.416	.402	.166	.284	.349	.462
IQ4	.114	.764	.405	.377	-.106	.390	.414	.358	.356	.403	.217	.249	.364	.450
IQ5	.129	.748	.370	.331	-.164	.374	.465	.419	.392	.381	.173	.261	.410	.438
IQ6	.120	.772	.351	.340	-.116	.336	.524	.408	.376	.341	.186	.225	.371	.436
IQ8	.146	.715	.335	.398	-.059	.363	.375	.340	.321	.398	.216	.243	.330	.347
IQ9	.092	.643	.354	.338	-.113	.345	.460	.408	.453	.392	.160	.218	.363	.382
IR1	.177	.439	.890	.392	-.150	.572	.382	.332	.343	.333	.244	.310	.391	.620
IR2	.178	.452	.895	.377	-.159	.539	.405	.377	.349	.324	.229	.295	.396	.606
IR3	.173	.428	.830	.340	-.017	.537	.409	.362	.352	.359	.282	.263	.353	.548
PQ1	.175	.416	.346	.824	-.016	.349	.339	.272	.298	.380	.321	.295	.439	.420
PQ2	.207	.272	.306	.699	.032	.280	.315	.302	.248	.325	.245	.242	.338	.274
PQ3	.185	.424	.365	.871	-.019	.367	.369	.295	.348	.402	.315	.288	.461	.432
PD2	.139	-.093	-.039	.057	.601	-.046	-.030	-.081	-.019	.044	.182	-.003	-.004	-.119
PD3	.151	-.142	-.135	-.020	.973	-.052	-.097	-.069	-.099	-.012	.109	-.089	-.048	-.165
PV1	.160	.418	.533	.377	-.058	.824	.418	.366	.316	.388	.243	.256	.386	.549
PV3	.236	.400	.512	.309	-.044	.824	.322	.307	.295	.263	.246	.308	.345	.554
PV4	.200	.371	.508	.340	-.038	.818	.373	.379	.329	.342	.263	.241	.406	.545
SQE1	.087	.514	.358	.309	-.139	.383	.726	.491	.428	.354	.164	.196	.386	.465
SQE2	.118	.455	.368	.362	-.083	.345	.774	.485	.441	.392	.147	.223	.323	.422
SQE3	.084	.263	.258	.203	.047	.248	.627	.437	.304	.369	.120	.091	.241	.264
SQE5	.088	.394	.298	.320	-.054	.291	.709	.448	.360	.411	.159	.170	.353	.340
SQR1	.074	.450	.314	.262	-.092	.295	.483	.725	.420	.336	.094	.109	.347	.334
SQR2	.059	.446	.320	.320	-.119	.331	.449	.738	.386	.366	.133	.166	.396	.344
SQR3	.108	.305	.282	.226	-.017	.292	.503	.722	.303	.356	.130	.117	.272	.310
SQR4	.108	.281	.270	.233	.008	.324	.474	.728	.237	.370	.133	.124	.302	.279
SQS2	.115	.467	.382	.338	-.103	.353	.512	.433	.914	.400	.200	.195	.383	.418
SQS3	.125	.451	.334	.336	-.058	.333	.469	.410	.887	.421	.242	.211	.366	.387
SVQ1	.130	.155	.181	.189	.060	.214	.344	.344	.218	*.450	.166	.082	.231	.137
SVQ3	.111	.377	.237	.321	-.043	.255	.384	.319	.354	.687	.191	.165	.307	.285
SVQ4	.078	.367	.286	.280	-.160	.276	.404	.380	.333	.618	.087	.170	.307	.331
SVQ7	.142	.421	.347	.403	.058	.343	.400	.375	.347	.846	.234	.255	.346	.341

Items	IC	IQ	IR	PQ	PD	PV	SQE	SQR	SQS	SVQ	TPS	UA	FQ	US
SVQ8	.141	.416	.312	.393	.037	.334	.402	.359	.365	.835	.287	.221	.350	.328
SVQ9	.130	.401	.288	.383	.049	.315	.400	.372	.350	.843	.229	.199	.367	.310
TPS1	.200	.139	.146	.200	.095	.171	.159	.104	.153	.171	.609	.160	.165	.099
TPS2	.316	.255	.291	.357	.139	.305	.215	.183	.236	.282	.905	.368	.283	.259
TPS3	.275	.198	.245	.335	.132	.259	.165	.146	.210	.239	.909	.326	.269	.211
TPS4	.264	.195	.262	.326	.108	.272	.167	.124	.214	.229	.916	.320	.263	.208
UA1	.423	.289	.288	.275	-.072	.278	.206	.155	.195	.207	.290	.830	.249	.295
UA2	.354	.255	.254	.269	-.085	.231	.201	.137	.195	.229	.262	.851	.249	.289
UA3	.359	.274	.287	.315	-.041	.302	.208	.152	.172	.217	.346	.821	.241	.322
FQ1	.184	.400	.358	.393	.008	.394	.375	.386	.333	.358	.264	.261	.836	.395
FQ2	.187	.342	.339	.404	-.029	.367	.316	.330	.304	.343	.242	.231	.839	.385
FQ3	.199	.449	.391	.493	-.082	.391	.456	.418	.397	.398	.235	.247	.827	.447
US1	.194	.491	.637	.415	-.138	.631	.455	.365	.394	.372	.224	.334	.448	.918
US2	.166	.541	.601	.451	-.181	.588	.524	.435	.424	.373	.215	.329	.452	.908

Notes: * = dropped for conservative improvement of discriminant validity (loading was below 0.600; only applied to SVQ1); IC = individualism–collectivism; IQ = information quality; IR = intention to reuse; PQ = picture quality; PV = perceived value; PD = power distance; TPS = third-party seals; SVQ = service quality; SQ = system quality; SQE = SQ: ease of use; SQR = SQ: reliability; SQS = SQ: security; UA = uncertainty avoidance; FQ = formatting quality; US = user satisfaction

Table B.3. Collinearity Statistics (Outer VIF Values)

Items	Outer VIF Values	Items	Outer VIF Values
IC1	1.576	SQR1	1.436
IC2	1.604	SQR2	1.454
IC3	1.104	SQR3	1.829
IQ1	2.394	SQR4	1.850
IQ2	2.419	SQS2	1.636
IQ3	2.451	SQS3	1.636
IQ4	1.902	SVQ3	1.478
IQ5	1.914	SVQ4	1.269
IQ6	2.088	SVQ7	2.388
IQ8	1.719	SVQ8	2.640
IQ9	1.440	SVQ9	2.652
IR1	2.285	TPS1	1.316
IR2	2.374	TPS2	2.674
IR3	1.706	TPS3	3.780
PQ1	1.662	TPS4	3.898
PQ2	1.223	UA1	1.602
PQ3	1.814	UA2	1.846
PD2	1.192	UA3	1.542
PD3	1.192	FQ1	1.694
PV1	1.515	FQ2	1.756
PV3	1.560	FQ3	1.498
PV4	1.535	US1	1.805
SQE1	1.255	US2	1.805
SQE2	1.362		
SQE3	1.220		
SQE5	1.298		

Table B.4. Zero-order Correlations and Interitem Correlational Diagnostics (n = 739)

Items	SQE1	SQE2	SQE3	SQE5	SQR1	SQR2	SQR3	SQR4	SQS2	SQS3
SQE2	.362**									
SQE3	.246**	.389**								
SQE5	.381**	.383**	.298**							
SQR1	.424**	.357**	.293**	.286**						
SQR2	.377**	.344**	.243**	.303**	.538**					
SQR3	.329**	.375**	.366**	.377**	.252**	.260**				
SQR4	.294**	.338**	.390**	.352**	.256**	.284**	.667**			
SQS2	.403**	.415**	.288**	.332**	.403**	.346**	.278**	.219**		
SQS3	.367**	.377**	.259**	.320**	.350**	.352**	.269**	.209**	.624**	
SQ (2nd order)	.634**	.667**	.611**	.632**	.644**	.628**	.665**	.644**	.660**	.632**

Notes: The bottom highlighted row shows the zero-order correlations of the latent construct's items against the overall average of the latent construct. The remaining items not highlighted are the inter-item correlational diagnostics. * = Correlation is significant at the 0.05 level (2-tailed). ** = Correlation is significant at the 0.01 level (2-tailed); n/s = correlation is insignificant; SQE = system quality ease of use; SQR = system quality reliability; SQS = system quality security

Table B.5. Measurement Model Statistics of All Latent Constructs (Part 1 of 2)

Latent construct	Mean	SD	1.	2.	3.	4.	5.	6.	7.	8.
1. Information quality (IQ)	4.093	.618	**.763**							
2. SQ ease-of-use (SQE)	3.960	.563	.485	**.711**						
3. SQ reliability (SQR)	3.953	.648	.504	.643	**.729**					
4. SQ security (SQS)	4.220	.717	.512	.464	.456	**.901**				
5. System quality (SQ) 2nd order	4.078	.542	.619	.799	.885	.716	N/A			
6. Picture quality (PQ)	3.868	.756	.475	.401	.362	.375	.455	**.801**		
7. Formatting quality (FQ)	3.923	.697	.485	.443	.450	.417	.521	.512	**.834**	
8. Service quality (SVQ)	3.756	.722	.523	.538	.470	.458	.572	.456	.435	**.780**
9. Perceived value (PV)	4.117	.660	.483	.397	.427	.386	.493	.415	.461	.393
10. User satisfaction (US)	4.281	.679	.559	.419	.433	.453	.546	.466	.490	.414
11. Third-party seals (TPSs)	3.731	.882	.237	.209	.165	.244	.235	.358	.284	.260
12. Intentions to reuse (IR)	4.227	.714	.501	.384	.407	.402	.491	.423	.433	.383
13. Individualism–collectivism (IC)	3.730	.721	.152	.097	.120	.122	.135	.243	.207	.147
14. Uncertainty avoidance (UA)	4.155	.664	.344	.199	.184	.236	.248	.355	.301	.267
15. Marker variable	3.142	.960	-.106	-.001	-.034	-.010	-.054	.072	.049	.061
16. Power distance (PD)	2.716	1.00	-.141	-.011	-.085	-.066	-.081	.027	-.026	-.004

Table B.5. Measurement Model Statistics of All Latent Constructs (Part 2 of 2)

Latent construct	Mean	SD	9.	10.	11.	12.	13.	14.	15.	16.
9. Perceived value (PV)	4.117	.660	**.822**							
10. User satisfaction (US)	4.281	.679	.669	**.913**						
11. Third-party seals (TPSs)	3.731	.882	.293	.222	**.845**					
12. Intentions to reuse (IR)	4.227	.714	.631	.677	.280	**.872**				
13. Individualism–collectivism (IC)	3.730	.721	.234	.168	.315	.176	**.744**			
14. Uncertainty avoidance (UA)	4.155	.664	.340	.372	.331	.340	.389	**.834**		
15. Marker variable	3.142	.960	.040	-.039	.074	-.024	.163	.037	N/A	
16. Power distance (PD)	2.716	1.00	-.059	-.170	.174	-.093	.217	-.056	.379	**.809**

Notes: Bolded and underlined numbers down the diagonal represent the square root of the AVEs.

Table B.6. Collinearity Statistics (Inner VIF Values) and Reliabilities for All Reflective Constructs

Latent Construct	# of Items	rho_A	CR	AVE	S_AVE	VIF
Information quality (IQ)	8	.901	.917	.582	.763	2.062
System Quality (SQ): ease of use (SQE)	4	.687	.803	.506	.711	2.342
SQ: reliability (SQR)	4	.707	.819	.531	.729	1.968
SQ: security (SQS)	2	.777	.896	.811	.901	1.652
Service quality (SVQ)	5	.846	.884	.608	.780	1.672
User satisfaction (US)	2	.803	.909	.834	.913	2.382
Perceived value (PV)	3	.761	.862	.676	.822	2.015
Intention to reuse (IR)	3	.845	.905	.761	.872	*
Formatting quality (FQ)	3	.784	.873	.696	.834	1.735
Picture quality (PQ)	3	.728	.842	.642	.801	1.723
Third-party seals (TPSs)	4	.910	.907	.714	.845	1.356
Uncertainty avoidance (UA)	3	.782	.873	.695	.834	1.540
Individualism–collectivism (IC)	3	.740	.786	.553	.744	1.380
Power distance (PD)	2	1.245	.782	.654	.809	1.145

Notes: AVE = average variance extracted; CR = composite reliability; S_AVE = square root of the AVE; VIF = inner variance inflation factor * could not be reported because this construct was used as the DV in the inner VIF calculations (all relationships ran against it).

Table B.7. Bootstrapped Confidence Interval Tests for Full and Partial Mediation Model

Proposed Relationship	Proposed Full Mediator	Mediation Test (ab)			Full/Partial Mediation Test (c′)			Type of mediation
		5% lower bound	95% upper bound	Include Zero?	2.5% lower bound	97.5% upper bound	Include Zero?	
IQ (a_1) → PV (b_1) → IR (c_1)	PV (b_1)	.047	.167	No	.168	.353	No	Partial
IQ (a_2) → US (b_2) → IR (c_1)	US (b_2)	.054	.198	No	.168	.353	No	Partial
SQ (a_3) → PV (b_1) → IR (c_2)	PV (b_1)	.077	.215	No	.176	.380	No	Partial
SQ (a_4) → US (b_2) → IR (c_2)	US (b_2)	.067	.218	No	.176	.380	No	Partial
SVQ (a_5) → PV (b_1) → IR (c_3)	PV (b_1)	.010	.105	No	(-.006)	.170	Yes	Full
SVQ (a_6) → US (b_2) → IR (c_3)	US (b_2)	(-.005)	.069	Yes	(-.006)	.170	Yes	n/a*

Notes: *Not a candidate for mediation because relationship between SVQ → US is insignificant; row 125 is the 5% lower bound point; row 4876 is the 95% upper bound point; IQ = information quality; IR = intentions to reuse; PV = perceived value; SQ = system quality; SVQ = service quality; US = user satisfaction

Table B.8. Comparing Latent Constructs' Means and Standard Deviations by Country

Country		**IQ**	**SQE**	**SQR**	**SQS**	**SQ**	**PQ**	**FQ**	**SVQ**
Kuwait	Mean	4.151	3.957	3.906	4.278	4.086	3.992	3.964	3.775
(*n* = 328)	SD	0.580	0.546	0.637	0.658	0.536	0.711	0.655	0.714
Poland	Mean	4.111	3.975	4.026	4.226	4.106	3.855	3.957	3.739
(*n* = 330)	SD	0.641	0.563	0.670	0.752	0.552	0.762	0.705	0.757
Latvia	Mean	3.771	3.905	3.845	3.956	3.924	3.422	3.620	3.745
(*n* = 80)	SD	0.582	0.637	0.567	0.756	0.509	0.745	0.764	0.613
Country		**PV**	**US**	**TPS**	**IR**	**IC**	**UA**	**MF**	**PD**
Kuwait	Mean	4.197	4.366	4.119	4.329	3.862	4.313	3.070	2.952
(*n* = 328)	SD	0.653	0.643	0.776	0.688	0.629	0.588	0.903	0.831
Poland	Mean	4.118	4.300	3.419	4.230	3.688	4.144	3.174	2.378
(*n* = 330)	SD	0.636	0.668	0.774	0.732	0.785	0.670	1.037	1.073
Latvia	Mean	3.785	3.844	3.442	3.797	3.372	3.575	3.300	3.169
(*n* = 80)	SD	0.686	0.718	1.073	0.578	0.647	0.602	0.829	0.849

Notes: IQ = information quality; IR = intention to reuse; PQ = picture quality; PV = perceived value; PD = power distance; TPS = third-party seals; SVQ = service quality; SQ = system quality; SQE = SQ: ease of use; SQR = SQ: reliability; SQS = SQ: security; UA = uncertainty avoidance; FQ = formatting quality; US = user satisfaction.

Table B.9. MANOVA Results on Latent Constructs by Country

Latent Construct	**Type III Sum of Squares**	**df**	**Mean Square**	***F***	**Sig.**
IQ	9.058	2	4.529	12.654***	0.000
SQE	0.199	2	0.099	0.309 (n/s)	0.734
SQR	2.655	2	1.327	3.157*	0.043
SQS	6.662	2	3.331	6.666***	0.001
SQ	1.784	2	0.892	3.019*	0.049
PQ	19.135	2	9.567	17.618***	0.000
FQ	7.886	2	3.943	8.210***	0.000
SVQ	0.114	2	0.057	0.109 (n/s)	0.897
PV	9.415	2	4.708	11.055***	0.000
US	14.753	2	7.376	17.461***	0.000
TPS	77.556	2	38.778	59.144***	0.000
IR	18.299	2	9.149	19.011***	0.000
IC	16.200	2	8.100	16.570***	0.000
UA	32.031	2	16.015	41.463***	0.000
PD	64.533	2	32.267	37.236***	0.000

Notes: *** $p <= 0.001$; ** $p <= 0.010$, * $p <= 0.050$; n/s = not significant; IQ = information quality; IR = intention to reuse; PQ = picture quality; PV = perceived value; PD = power distance; TPS = third-party seals; SVQ = service quality; SQ = system quality; SQE = SQ: ease of use; SQR = SQ: reliability; SQS = SQ: security; UA = uncertainty avoidance; FQ = formatting quality; US = user satisfaction

Table B.10. Tukey's HSD Comparisons

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
IQ	Kuwait	Poland	0.056 (n/s)	0.049	0.478	-0.058	0.171
		Latvia	0.409***	0.082	0.000	0.218	0.601
	Poland	Kuwait	-0.056 (n/s)	0.049	0.478	-0.171	0.058
		Latvia	0.353***	0.082	0.000	0.160	0.546
	Latvia	Kuwait	-0.409***	0.082	0.000	-0.601	-0.218
		Poland	-0.353***	0.082	0.000	-0.546	-0.160
SQE	Kuwait	Poland	-0.023 (n/s)	0.046	0.873	-0.131	0.085
		Latvia	0.034 (n/s)	0.077	0.898	-0.147	0.216
	Poland	Kuwait	0.023 (n/s)	0.046	0.873	-0.085	0.131
		Latvia	0.057 (n/s)	0.078	0.744	-0.126	0.240
	Latvia	Kuwait	-0.034 (n/s)	0.077	0.898	-0.216	0.147
		Poland	-0.057 (n/s)	0.078	0.744	-0.240	0.126
SQR	Kuwait	Poland	-0.112 (n/s)	0.053	0.087	-0.235	0.012
		Latvia	0.061 (n/s)	0.088	0.772	-0.147	0.268
	Poland	Kuwait	0.112 (n/s)	0.053	0.087	-0.012	0.235
		Latvia	0.172 (n/s)	0.089	0.129	-0.037	0.381
	Latvia	Kuwait	-0.061 (n/s)	0.088	0.772	-0.268	0.147
		Poland	-0.172 (n/s)	0.089	0.129	-0.381	0.037
SQS	Kuwait	Poland	0.040 (n/s)	0.057	0.764	-0.095	0.175
		Latvia	0.350***	0.096	0.001	0.124	0.576
	Poland	Kuwait	-0.040 (n/s)	0.057	0.764	-0.175	0.095
		Latvia	0.310**	0.097	0.004	0.082	0.538
	Latvia	Kuwait	-0.350***	0.096	0.001	-0.576	-0.124
		Poland	-0.310**	0.097	0.004	-0.538	-0.082
SQ	Kuwait	Poland	-0.023 (n/s)	0.044	0.866	-0.126	0.081
		Latvia	0.160 (n/s)	0.074	0.080	-0.014	0.334
	Poland	Kuwait	0.023 (n/s)	0.044	0.866	-0.081	0.126
		Latvia	0.182*	0.075	0.039	0.007	0.357
	Latvia	Kuwait	-0.160 (n/s)	0.074	0.080	-0.334	0.014
		Poland	-0.182*	0.075	0.039	-0.357	-0.007
PQ	Kuwait	Poland	0.130 (n/s)	0.060	0.076	-0.010	0.271
		Latvia	0.594***	0.100	0.000	0.358	0.830
	Poland	Kuwait	-0.130 (n/s)	0.060	0.076	-0.271	0.010
		Latvia	0.464***	0.101	0.000	0.226	0.701
	Latvia	Kuwait	-0.594***	0.100	0.000	-0.830	-0.358
		Poland	-0.464***	0.101	0.000	-0.701	-0.226
FQ	Kuwait	Poland	0.021 (n/s)	0.056	0.923	-0.111	0.154
		Latvia	0.375***	0.094	0.000	0.153	0.597
	Poland	Kuwait	-0.021 (n/s)	0.056	0.923	-0.154	0.111
		Latvia	0.354***	0.095	0.001	0.130	0.577
	Latvia	Kuwait	-0.375***	0.094	0.000	-0.597	-0.153
		Poland	-0.354***	0.095	0.001	-0.577	-0.130
SVQ	Kuwait	Poland	0.026 (n/s)	0.059	0.898	-0.112	0.164
		Latvia	0.027 (n/s)	0.099	0.960	-0.205	0.259
	Poland	Kuwait	-0.026 (n/s)	0.059	0.898	-0.164	0.112
		Latvia	0.001 (n/s)	0.099	1.000	-0.232	0.234
	Latvia	Kuwait	-0.027 (n/s)	0.099	0.960	-0.259	0.205
		Poland	-0.001 (n/s)	0.099	1.000	-0.234	0.232
PV	Kuwait	Poland	0.085 (n/s)	0.053	0.245	-0.040	0.209
		Latvia	0.417***	0.089	0.000	0.209	0.626

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
	Poland	Kuwait	-0.085 (n/s)	0.053	0.245	-0.209	0.040
		Latvia	0.332***	0.089	0.001	0.122	0.543
	Latvia	Kuwait	-0.417***	0.089	0.000	-0.626	-0.209
		Poland	-0.332***	0.089	0.001	-0.543	-0.122
US	Kuwait	Poland	0.058 (n/s)	0.053	0.510	-0.066	0.182
		Latvia	0.521***	0.089	0.000	0.313	0.729
	Poland	Kuwait	-0.058 (n/s)	0.053	0.510	-0.182	0.066
		Latvia	0.462***	0.089	0.000	0.253	0.671
	Latvia	Kuwait	-0.521***	0.089	0.000	-0.729	-0.313
		Poland	-0.462***	0.089	0.000	-0.671	-0.253
TPS	Kuwait	Poland	0.686***	0.066	0.000	0.532	0.841
		Latvia	0.654***	0.110	0.000	0.395	0.913
	Poland	Kuwait	-0.686***	0.066	0.000	-0.841	-0.532
		Latvia	-0.032 (n/s)	0.111	0.955	-0.293	0.229
	Latvia	Kuwait	-0.654***	0.110	0.000	-0.913	-0.395
		Poland	0.032 (n/s)	0.111	0.955	-0.229	0.293
IR	Kuwait	Poland	0.106 (n/s)	0.056	0.145	-0.026	0.238
		Latvia	0.583***	0.095	0.000	0.361	0.805
	Poland	Kuwait	-0.106 (n/s)	0.056	0.145	-0.238	0.026
		Latvia	0.477***	0.095	0.000	0.253	0.700
	Latvia	Kuwait	-0.583***	0.095	0.000	-0.805	-0.361
		Poland	-0.477***	0.095	0.000	-0.700	-0.253
IC	Kuwait	Poland	0.190**	0.057	0.002	0.057	0.323
		Latvia	0.519***	0.095	0.000	0.295	0.743
	Poland	Kuwait	-0.190**	0.057	0.002	-0.323	-0.057
		Latvia	0.329**	0.096	0.002	0.104	0.554
	Latvia	Kuwait	-0.519***	0.095	0.000	-0.743	-0.295
		Poland	-0.329**	0.096	0.002	-0.554	-0.104
UA	Kuwait	Poland	0.158**	0.050	0.005	0.039	0.277
		Latvia	0.770***	0.085	0.000	0.571	0.969
	Poland	Kuwait	-0.158**	0.050	0.005	-0.277	-0.039
		Latvia	0.612***	0.085	0.000	0.411	0.812
	Latvia	Kuwait	-0.770***	0.085	0.000	-0.969	-0.571
		Poland	-0.612***	0.085	0.000	-0.812	-0.411
PD	Kuwait	Poland	0.584***	0.076	0.000	0.407	0.762
		Latvia	-0.186 (n/s)	0.127	0.307	-0.484	0.112
	Poland	Kuwait	-0.584***	0.076	0.000	-0.762	-0.407
		Latvia	-0.770***	0.128	0.000	-1.070	-0.470
	Latvia	Kuwait	0.186 (n/s)	0.127	0.307	-0.112	0.484
		Poland	0.770***	0.128	0.000	0.470	1.070

Notes: *** $p <= 0.001$; ** $p <= 0.010$, * $p <= 0.050$; n/s = not significant; IQ = information quality; IR = intention to reuse; PQ = picture quality; PV = perceived value; PD = power distance; TPS = third-party seals; SVQ = service quality; SQ = system quality; SQE = SQ: ease of use; SQR = SQ: reliability; SQS = SQ: security; UA = uncertainty avoidance; FQ = formatting quality; US = user satisfaction

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[i] The difference is that items within *formative constructs* are theoretically distinct and thus are not replaceable with other items in the same construct; items in *reflective constructs* are theoretically the same and thus are replaceable with each other (Diamantopoulos & Winklhofer, 2001). This distinction has recently become a serious issue in systems-related research where it has been discovered that many previous studies have been mis-specified because they did not distinguish between reflective and formative constructs (Petter et al., 2007). Such mis-specification can lead to problems in empirical results and theoretical interpretations, including the potential increase in both Type I and Type II errors (Petter et al., 2007).

[ii] The basic standard followed here is that the square root of the AVE for any given construct (latent variable) should be higher than any of the correlations involving the construct (Fornell & Larcker, 1981; Staples et al., 1999). The numbers are shown in the diagonal for constructs (bolded and underlined).

[iii] Validating items within formative measures is particularly challenging because these items can move in different directions apart from each other. Whereas reflective indicators must demonstrate considerably high correlations among each other (i.e., exhibit high conceptual overlap) to be valid internally, the indicators of a formative construct need not meet this criterion, and instead need to represent distinct facets of the overall construct being modeled (Bollen & Lennox, 1991; Diamantopoulos & Winklhofer, 2001; Petter et al., 2007). Reflective items are interchangeable but formative items are not interchangeable; hence, reliability measurements are not appropriate for formative constructs (Diamantopoulos & Winklhofer, 2001). Specifically, internal consistency examinations of formative constructs with Cronbach's α and average variance extracted (AVE) calculations are not methodologically appropriate (Bagozzi, 1994; Cenfetelli & Bassellier, 2009; Petter et al., 2007). Researchers have traditional used theoretical reasoning alone to support the validity of formative constructs (Diamantopoulos & Winklhofer, 2001). Over time, methodological approaches have emerged to improve validation of formative constructs, such as using the modified multitrait-multimethod (MTMM) approach and assessing multicollinearity (Petter et al., 2007; Straub et al., 2004).

[iv] It would be more ideal to do this using a MIMMIC model where all the formative items of a second-order construct were correlated to the average of a separately created reflective construct representing overall second-order construct. However, we had no such reflective meta-constructs available from the literature.