



Extending the Theory of Planned Behavior in the Social Commerce Context: A Meta-Analytic SEM (MASEM) Approach

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Abstract

The theory of planned behavior (TPB) is popular in social commerce research, but existing studies have yielded inconclusive and inconsistent findings. As TPB was developed before the introduction of the Internet, Web 2.0 technologies, and social media, it is time to evaluate whether its relevance, effectiveness, novelty, and parsimony may have deteriorated due to temporal factors and the emergence of new Information Systems (IS) artifacts. In this work, an extended TPB2 is proposed by integrating social support, and MASEM analysis was conducted using a pooled correlation matrix. The findings revealed that TPB2 can better capture the nature of social commerce, as it can explain 28.4% of the variance in attitude, 59.0% of the variance in behavioral intention, and 9% of the variance in use behavior. In addition, it indicates that masculinity and uncertainty avoidance are the most significant Hofstedian cultural dimensions. The theoretical and managerial implications are also discussed along with the research agenda.

Keywords Social commerce · Theory of Planned Behavior (TPB) · TPB2 · Meta-analytic SEM (MASEM) · Cultural differences · Hofstedian cultural dimensions

1 Introduction

The emergence of social media and Web 2.0 has allowed consumers to create content as well as share reviews and recommendations (Liao et al., 2021). Social media (e.g., Instagram, Facebook, etc.), together with Web 2.0, have enabled user-generated content and social interactions and this has triggered the creation of an innovative form of

online business transaction coined as social commerce or s-commerce (Leong et al., 2021b). S-commerce facilitates information sharing and the extension of recommendations among consumers (Algharabat & Rana, 2021). The s-commerce field has expanded drastically in the past few years and has become a key research area (Al-Omouh et al., 2022). There is an increasing number of vendors launching s-commerce initiatives due to the promising outcomes

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(Mikalef et al., 2021). As the birth of s-commerce has led to big changes for not only businesses but also consumers, understanding consumers' motivations in the s-commerce context may help businesses to enhance their potential (Busalim et al., 2021).

The business potential for s-commerce is indeed promising as its value is expected to reach 84.2 billion USD in 2024, contributing to the U.S. retail e-commerce sales by 7.8% (Tugba Sabanoglu, 2020). The market size value for 2030 is anticipated to reach 6.2 trillion USD (Grand View Research, 2022) and is forecasted to grow by 2051.49 billion USD between 2020 and 2024 (Technavio, 2021). The first academic document that made reference to "social commerce" was published in 2006 and on July 29th, 2009, s-commerce was formally launched with Flowers.com as its first Facebook shop (Alsaour, 2020). According to Dwivedi et al. (2021), social commerce is a combination of commercial and social activities, whereas Algharabat and Rana (2021) referred to social commerce as an amalgamation of social media and the Internet that aims to enrich people's engagements in the sale and marketing of various products within online communities. Generally, s-commerce is defined as "an extension of e-commerce sites, integrated with social media and Web 2.0 technology to encourage online purchases and interactions with customers before, during, and after the purchase" (Meilatinova, 2021, p. 1). This social interaction has altered e-commerce, transforming it into a novel business paradigm known as social commerce, which refers to online commerce applications that utilize social media and Web 2.0 technologies (Busalim et al., 2021). These technologies have shifted e-commerce from a product-based platform to a user-centered platform (Guo et al., 2020).

The main goal of s-commerce research is to ascertain whether consumer purchasing behavior is different in e-commerce relative to other channels, that is, if certain features of s-commerce have influenced the intention to purchase. As consumers' purchasing behavior is assumed to be rational, a popular theory for analyzing consumers' attitudes and purchase intentions is the theory of planned behavior (TPB). It has been applied in prior studies, albeit with inconsistent findings, as certain factors may be significant in some studies but are insignificant in others (Berki-Kiss & Menrad, 2022; Dionysis et al., 2022; Gvili & Levy, 2021; Tewari et al., 2022). Besides, there are temporal effects on the TPB performance. For example, the effect of perceived behavioral control (PBC) on behavioral intention decreases over time (Fischer & Karl, 2022). Extant literature has also indicated that some relationships may lose their relevance or importance over time (Blut et al., 2022). Similarly, the effects of TPB may vary across various cultures (Morren & Grinstein, 2021). To reach a conclusive result and to examine whether the effect of different factors may vary over time and across

different cultures, there is a need to consolidate prior studies and ascertain the consistency of TPB through meta-analyses. The findings yielded by such investigations would allow an extended TPB model to be proposed and supported.

The motivations for this study are multi-faceted. First, the original TPB (Ajzen, 1991) was first introduced in 1991, and was thus 30 years old by the time the Internet and social media became popular. Over that period, online social behavior has substantially changed and therefore there is indeed a need to revisit and enhance the TPB to keep the theory relevant and parsimonious in the current context.

Second, even though numerous studies have been conducted with the aim of determining the factors that influence s-commerce adoption, these studies have produced contradictory and inconsistent results, precluding meaningful generalization of the findings (Dwivedi et al., 2021). For example, findings yielded by some studies (e.g., Hung et al., 2018; Pujadas-Hostench et al., 2019a; Sanne & Wiese, 2018) supported the significant relationship between attitude and intention, while others (e.g., Hansen et al., 2018; Ho & Rezaei, 2018) indicated that the relationship was not significant. Similarly, some studies supported the relationship between PBC and intention (e.g., Lin & Wu, 2015; Pujadas-Hostench et al., 2019b; Smith et al., 2014) which is not supported by the work of Sanne and Wiese (2018). Likewise, there was a significant effect of subjective norms (SN) on intention in some studies (e.g., Qin et al., 2018; Sanne & Wiese, 2018; Zhang et al., 2015) while in others (e.g., Hung et al., 2018; Pujadas-Hostench et al., 2019a) no significant effect was found. Therefore, there is a need to aggregate previous findings to provide a clear and convincing understanding of the effects of TPB on s-commerce intention to scholars and practitioners. To address this problem, a MASEM study should be conducted, as it is suitable for synthesizing and confirming the role of TPB, as well as ascertaining whether the inconsistencies are caused by differences in research methods, samples, and/or the model itself.

Third, the popularity of social commerce evolves over time and has become particularly significant in the recent decade. We thus need to investigate the temporal moderating effect to examine whether the popularity of s-commerce as indicated by the year of publication may affect the value of the theory. The findings regarding whether the effect sizes remain constant, decline, or get stronger over time may indicate the effect of s-commerce popularity on consumers' purchase behavior.

Finally, as s-commerce involves extensive interactions among consumers that may be culture-related, there is also a need to examine the effects of TPB across various cultures to determine whether there are cultural differences based on a consolidated dataset comprising of various studies included in the meta-analysis (Pavlou, 2002). In addition to that, in

this work, we also examined the mediating effects of attitude and intention in the revised model in order to ascertain whether there are competitive or complementary mediation effects of the mediators of TPB. Thus, this study also serves as a comparative exploration of the role of different cultures in s-commerce intention. Moreover, we also need to integrate prior findings associated with TPB in s-commerce. Currently, there are only three systematic reviews on s-commerce (Esmaceli & Hashemi, 2019; Han et al., 2018; Sarker et al., 2020). However, a systematic review is different from MASEM as it only involves descriptive analyses, without any confirmation or validation of the causality of the relationships in the research framework or theory testing (Tamilmani et al., 2021b). Therefore, this study will fill the void in the extant literature on s-commerce and provide important empirical evidence to synthesize and verify the overall effects of TPB in predicting s-commerce intention.

More importantly, based on the MASEM analysis, we have also successfully developed and validated the TPB2 by using s-commerce as empirical evidence. The use of a specific context to verify and extend a theory is similar to the strategy adopted by Tamilmani et al. (2021a) who chose findings related to social commerce as the empirical evidence to validate and evaluate the unified theory of acceptance and use of technology 2 (UTAUT2) model. S-commerce was chosen as it entails electronic word-of-mouth (eWoM), social media, user-generated content (UGC), Web 2.0, online reviews, and online user interactions, which did not exist in the IS setting when the original TPB was developed in 1991.

The use of MASEM is superior to traditional meta-analysis as it can test not only the bivariate relationships but also the mediation or indirect effects that involve at least three variables, none of which is possible in traditional meta-analyses. Furthermore, the MASEM method is better than traditional meta-analysis as it pools thousands of observations that are significantly greater than the sample size for SEM to synthesize the overall effects for the whole field of study. Thus, it can better evaluate structural parameters and bolster the statistical power of the research model (Liang et al., 2021).

The remainder of this paper is presented in the following sequence. The next section presents a literature review and an explanation of the TPB theory before elaborating on the development of our hypotheses and research model. This is followed by the research method of the meta-analytic SEM analysis. The MASEM results for the original TPB, the initial TPB1, and the final TPB2 are presented next. Finally, our findings are discussed, along with their practical and theoretical implications, before presenting the study limitations and proposing future directions in this research domain.

2 Literature Review

2.1 TPB and Social Commerce Intention

TPB (Fig. 1) was developed by Ajzen (1991) for predicting and explaining intentions and use behaviors as an improvement to the theory of reasoned action (TRA). TPB entails three independent core variables—SN, attitude (AT), and PBC as the new variable—and its aim is to ascertain whether these three key constructs influence users' intentions and ultimately their behaviors (Hung et al., 2018).

Perceived behavioral control refers to the user's ability to engage in some forms of behavior while subjective norms refer to the effect of information, as well as normative and external factors, while attitude refers to beliefs with regards to predictive behavior (Ajzen, 1991). TPB theorizes that the more favorable the subjective norms, attitude, and perceived behavioral control, the more intense the intent to exhibit a behavior would be (Jokonya, 2017).

TPB has been extensively used in numerous domains, including psychology, sociology, management, and information systems (Jokonya, 2017). Moreover, TPB is the dominant theory in IS research in examining the effect of users' intention to engage in a specific behavior (Jokonya, 2016). For instance, TPB has been used to examine consumers' intention to adopt s-commerce. Appendix Table 11 shows a summary of the findings yielded by our literature search, which will be enlightened in more detail in the following section. The findings showed inconclusive, mixed, and scattered results. For example, some studies show significant paths while others show otherwise.

The inconclusive mixed findings and inconsistencies can be seen from the contradictory outcomes of the existing social commerce studies based on TPB (Appendix Table 11). Some studies showed a significant effect of attitude on behavioral intention (Bojei & Abu, 2016; Ghosh, 2019; Hajli et al., 2015; Hung et al., 2018; Liébana-Cabanillas et al.,

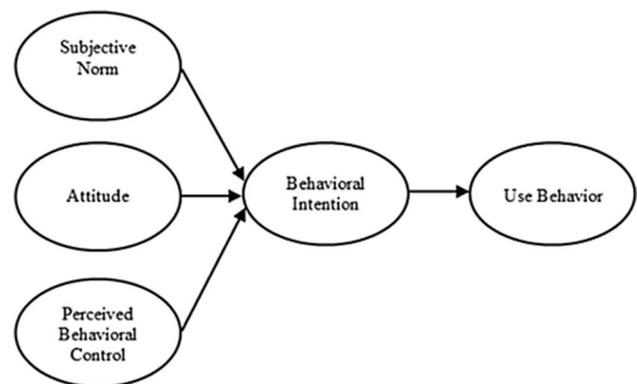


Fig. 1 The original TPB model

2014; Lin & Wu, 2015; McLaughlin & Stephens, 2019; Pujadas-Hostench et al., 2019a, b; Sanne & Wiese, 2018; Shin, 2013; Smith et al., 2014; Yeon et al., 2019), while others showed no significant effect (Hansen et al., 2018; Ho & Rezaei, 2018). Furthermore, there is a significant relationship between subjective norms and behavioral intention (Akman, 2015; Bojei & Abu, 2016; Hajli et al., 2015; Ho & Rezaei, 2018; Hong et al., 2019; Liébana-Cabanillas et al., 2018; Lin & Wu, 2015; McLaughlin & Stephens, 2019; Pujadas-Hostench et al., 2019b; Qin et al., 2018; Sanne & Wiese, 2018; Shin, 2013; Smith et al., 2014; Zhang & Wang, 2019) but Hung et al. (2018) found no significant effect.

Furthermore, there are marked differences in the strengths of the relationships, which can be seen from the minimum and maximum values of the correlation coefficients in Appendix Table 11. For instance, the correlation coefficients between attitude and behavioral intention span from -0.080 to 0.803, while the range for the correlation coefficients between perceived behavioral control and behavioral intention is between 0.116 and 0.809. Besides, the correlation coefficients between subjective norms and behavioral intention range from 0.015 to 0.972, while the correlation coefficients between behavioral intention (BI) and use behavior (UB) span from 0.210 to 0.833.

Besides, the order of strengths of the TPB constructs also varies across studies. For instance, Bojei and Abu (2016) found that perceived behavioral control is the strongest predictor for BI followed by attitude and subjective norms. However, Hajli et al. (2015) found that subjective norms are the strongest antecedent of behavioral intention followed by attitude and perceived behavioral control. On the other hand, Lin and Wu (2015) found that attitude is the strongest predictor of behavioral intention followed by perceived behavioral control and subjective norms. These findings show that, although TPB has been used extensively in many fields of study, its effects in the s-commerce context remain inconsistent.

Another issue is that TPB assumes that the three core variables are independent of each other. This is unrealistic in the real case, as perceived behavioral control can certainly affect both attitude and subject norms. This is evidenced by the high correlations among these constructs and is often discussed in the literature as a common method bias. The discovery of these potential new links among the TPB constructs is vital as it can provide new theoretical contributions and better understanding of TPB to scholars and theorists. It can also enhance the predictive power of the extended TPB model in terms of its effect size and the percentage of variance explained. The additional paths will make the TPB model more relevant, complete, comprehensive, and parsimonious. Therefore, there is an urgent need to synthesize and validate the overall effect of the TPB theory to ascertain whether there are indeed insignificant paths, new paths, or

potential inconsistencies in TPB due to the cultural differences, variations in sampling, research methods, or temporal deterioration of the theory.

Attitude is represented by a mathematical function of cognitive beliefs that implies a negative or positive feeling about exhibiting a particular behavior (Pujadas-Hostench et al., 2019b). As proposed in TPB, attitude is the antecedent of behavioral intention, which is defined as the degree to which a consumer judges the behavior as negative or positive (Ajzen, 1991). Prior studies from different contexts have shown a strong relationship between attitude and intention (Hsu et al., 2014; Kim et al., 2016; Ruiz-Mafe et al., 2014; Sanne & Wiese, 2018; Tariq et al., 2017). According to Al-Debei et al. (2013), a more positive attitude towards a particular behavior will lead to a stronger intention to exhibit that behavior. Therefore, it is anticipated that a positive attitude among s-commerce consumers will trigger a greater possibility of intention to adopt s-commerce.

Prior studies have also indicated that subjective norms are a strong antecedent of behavioral intention (Shavneet Sharma et al., 2021; Shin, 2013). An individual may consider and weigh the contribution of opinion given by a referent to determine whether to comply with the referent's wishes. Therefore, subjective norms may be equated with the individual's motivation and perception evaluation of all related referents. Thus, subjective norms are a primary antecedent of the unique attribute of social network services such as s-commerce (Shin & Kim, 2008). There is a positive influence of subjective norms on s-commerce intention (Shin, 2013; Shwadhin Sharma & Robert, 2014). In the s-commerce environment, individuals are exposed to intense influence from the online communities, and their decisions are therefore greatly influenced by the advice and opinions of the referents. These may include the individuals' perceptions of what others may think about their engagements in s-commerce, the discussion on the buying of goods and services, or whether it is considered fit by other people (Javadi et al., 2019). Hence, we foresee that subjective norms will have a significant impact on s-commerce intention.

The user's behavioral intention is considered a direct determinant of use behavior and is applied in TPB to predict actual behavior (Ho et al., 2015). Behavioral intention is defined as the amount of effort a consumer is prepared to expend to exhibit a particular behavior (Sanne & Wiese, 2018). The relationship between behavioral intention and use behavior in the social media context has been demonstrated in previous studies (Al-Debei et al., 2013; Baker & White, 2010; Leng et al., 2011). Therefore, we expect that the stronger the intention to adopt s-commerce among consumers, the higher the actual usage would be. Hence, based on the justifications presented above, we formulated the following hypothesis:

H1: TPB is valid as a baseline model.

2.2 The TPB1 model

Though TPB has been applied extensively in many contexts, there are still many inconsistencies in the findings yielded. Besides, TPB assumes that SN, AT, and PBC are independent of each other. However, in the real scenario, these variables are not independent, as indicated by the high correlations between them. Therefore, there is a need to extend TPB to address these issues. Hence, to increase its explanatory power, we have proposed the initial TPB1 model with additional path associations that can further enhance the parsimony, relevance, and comprehensiveness of the theory. The application of a new internal mechanism which refers to the enrichment of the existing model's latent variables through new path associations to extend the model is in line with the strategy adopted by Tamilmani et al. (2021b).

In s-commerce, consumers tend to recommend goods or services to friends and family if they are content with the purchase (Ho & Rezaei, 2018). Subjective norms influence consumers' attitudes towards sharing experience and knowledge (Schepers & Wetzels, 2007). Venkatesh and Davis (2000) asserted that "subjective norm has a significant influence on attitude towards an intended behavior when an individual internalizes the social influence imposed on him/her" (p. 187). Similarly, Bock et al. (2005) opined that an individual will not exhibit a behavior if he or she believes that the behavior would not be condoned by the community. Prior research has indicated that subjective norms exert a significant impact on attitude (Ajzen, 2002; Hong et al., 2019; Lin & Wu, 2015; Venkatesh & Davis, 2000; Yeo et al., 2017). As consumers are exchanging knowledge about goods and services in the social media setting, we anticipate that they can be influenced by the norms that exist in the online community. Therefore, their attitudes are most likely to be group-driven (Ho & Rezaei, 2018), leading to the following hypothesis:

H2.1: Subjective norms have a significant impact on attitudes towards s-commerce.

An individual's behavior is an outcome of reasonable activity to realize the behavior externally and assess the information internally (Kim & Moon, 2019). This behavior can be influenced by subjective norms (Friedrich, 2016), which denote the social effect of groups of individuals within the online communities (Chu & Chen, 2016). In s-commerce, through social interactions, individuals are exposed to the social influences of others in terms of advice, opinions, recommendations, and reviews on the purchase of products or services (Ng, 2013). Therefore, as their use

behaviors are influenced by these subjective norms, we theorized that:

H2.2: Subjective norms have a significant influence on s-commerce use behavior.

Chung et al. (2012) opined that perceived behavioral control is associated with the formation of attitude. Consumers tend to depend on the awareness of behavioral control when making purchase decisions because their perceptions tend to expose their beliefs on the evaluation of the product and their subsequent competence to control the behavior (Chung et al., 2012). Hence, their attitude will be more positive if they are in control. The psychology literature has shown that an individual's perceived behavioral control can affect behavior and emotion (Skinner et al., 1988). Moreover, Baronas and Louis (1988) asserted that individuals' perceived control of their surroundings may trigger favorite outcomes such as information systems acceptance. In s-commerce, consumers' perceived control can trigger their desire to share information through the s-commerce platforms and this is especially important for their decision-making on whether to disclose information via these platforms (Krasnova et al., 2010; Lin et al., 2013). A greater perceived information control will lead to a more positive attitude because consumers will have fewer worries about data disclosure when sharing personal information (Hajli & Lin, 2016). Moreover, perceived behavioral control significantly influences attitude toward channel migration (Pookulangara & Natesan, 2010) and tax-paying (Ratnawati et al., 2017). With the addition of three new relationships, we expect that the TPB1 model will have higher predictive power than the baseline TPB model. Thus, we postulate that:

H2.3: Perceived behavioral control has a significant influence on attitude toward s-commerce.

H2.4: TPB1 is superior to TPB in terms of interpretability and percentage of variance explained.

Even though TPB has been used extensively in various fields of study, researchers' understanding of how planned behavior changes over time remains very limited (Suh & Hsieh, 2016). This shortcoming has impeded their ability to take into consideration the temporal effect in the research design when observing the behavioral changes. TPB suggests that behavioral intention is the precursor of actual behavior. However, when an individual says that he or she will perform a planned behavior in the future, this does not mean that he or she will necessarily do so, as intentions may change over time (Suh & Hsieh, 2016). Thus far, TPB has not been extended to include these temporal effects even though several studies have indicated a reduction in its predictive power in predicting behavior in distant

future (Conner et al., 2000; McEachan et al., 2011). Suh and Hsieh (2016) found that behavioral intention reduces by 15–20% when the planned behavior is expected to be executed after a few weeks compared to a temporal lag of only a few days. Therefore, we anticipate that the effects of the core independent constructs in TPB will change over time, as reflected in the following hypothesis:

H3: There is a temporal effect on the TPB1 model.

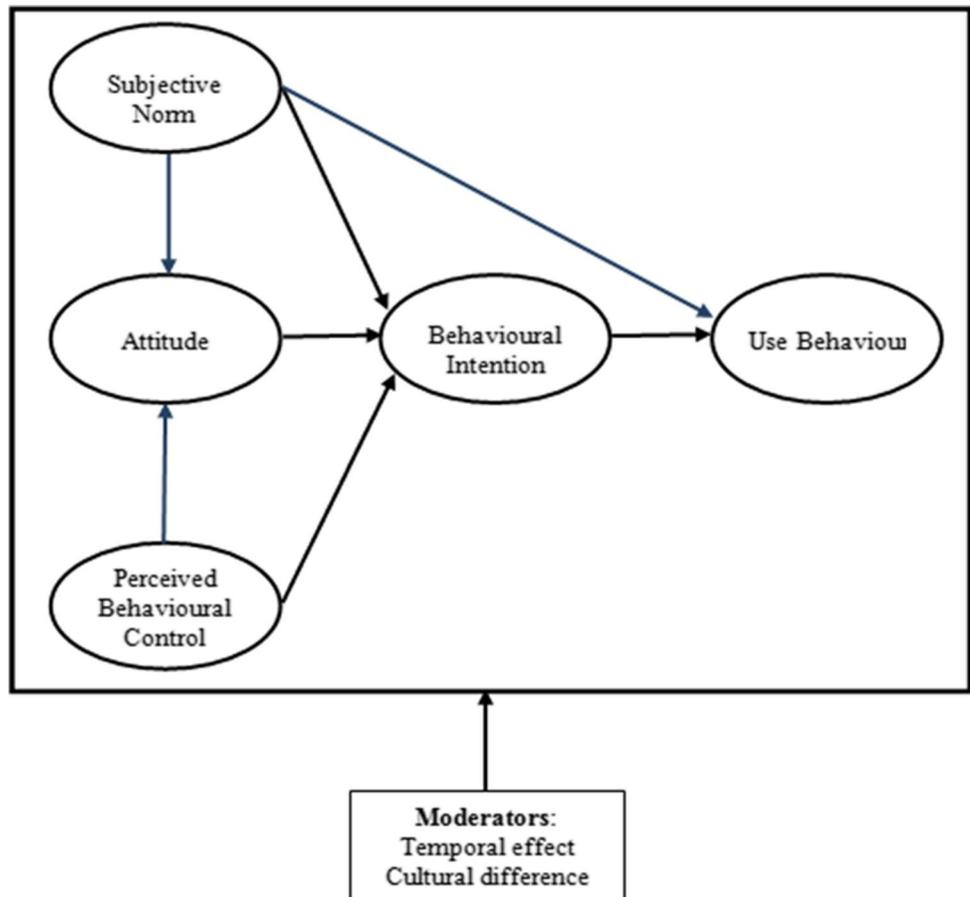
Ajzen (1991) asserted that the predictive patterns of the TPB constructs should be universal, consistent, and generalizable for a particular behavior across various samples. However, the author was also aware that sample-specific variations may occur. For example, the relationships in TPB may be moderated by intention stability and personality (Rhodes et al., 2002; Sheeran & Abraham, 2003). Studies have shown that most of the psychological constructs will vary due to diversity in social values across different cultures (Hagger et al., 2007). Culture also moderates the relationship between prior average ratings and customers' ratings (Wang et al., 2021). The differences in the degree of collectivism or individualism has been identified as the central construct that contributes to cultural differences.

Cross-cultural studies have shown that national groups are likely to endorse either individualism or collectivism (Rhodes et al., 2002). For instance, Asian people have greater propensity for collectivism while European people place greater value on individualism (Markus & Kitayama, 1991). Previously, the effects of cultural differences based on specific countries (i.e., the United Kingdom, Estonia, Hungary, Greece, Singapore, the Netherlands, and the EU nations) on TPB have been examined in relation to physical activity, job seeking, online shopping, green purchase behavior, and smoking cessation (Choi & Geistfeld, 2004; Hagger et al., 2007; Hassan & Shiu, 2017; Liobikiene et al., 2016; Van Hooft et al., 2006). However, thus far, no meta-analytic collective comparison between the Eastern and the Western cultures has been conducted. Because of the extensive differences between the two cultures, it is extremely important to determine whether the generalizability of TPB is universal. Thus, in this work, we test the following hypothesis based on the data obtained through meta-analysis:

H4: There are effects of cultural differences in the TPB1 model.

Hence, we proposed a TPB1 model (Fig. 2) as follows:

Fig. 2 The TPB1 model. Note: Blue arrows indicate new relationships



3 Research Method

In the present study, we adopted an integrated two-stage random effect correlation-based meta-analysis-structural equation modeling (MASEM) technique to evaluate the TPB, TPB1, and TPB2 models.

3.1 Meta-analysis

The aims of the meta-analysis are multifold. First, it synthesizes the overall effect sizes for the constructs in the TPB model. Second, it verifies and clarifies the inconsistencies in the structural path findings yielded by the existing studies. Third, it evaluates the magnitude of the structural causal relationships in TPB. Fourth, it tests the moderating effect of cultural differences between the East and the West, as well as the temporal moderating effect of publication time-lag. Finally, it assesses the mediating effects of the mediators in the two models.

Meta-analysis enables researchers to test a theory by accumulating and synthesizing the true effect sizes of the relationships from multiple studies (Paré et al., 2015; Templier & Paré, 2018). Prior literature has shown that meta-analysis is an invaluable instrument for research syntheses, as it enables the use of statistical techniques to correct measurement and sampling errors, as well as the inclusion of inconsistent and insignificant results (Dwivedi et al., 2019). Compared to the conventional approach of obtaining common inferences based on existing studies via narrative review, meta-analysis offers rather rigorous, unbiased, and trustworthy inferences (Wu & Du, 2012). Before the meta-analysis, a six-step framework shown in Fig. 3 was applied in this study to gather the pertinent data (Cram et al., 2020; Templier & Paré, 2015).

3.2 Formulating the Problem

We defined the objectives of the review and identified the main TPB constructs for the meta-synthesis. This strategy was based on the research questions that may guide the type

of information to be searched and the selection of relevant literature.

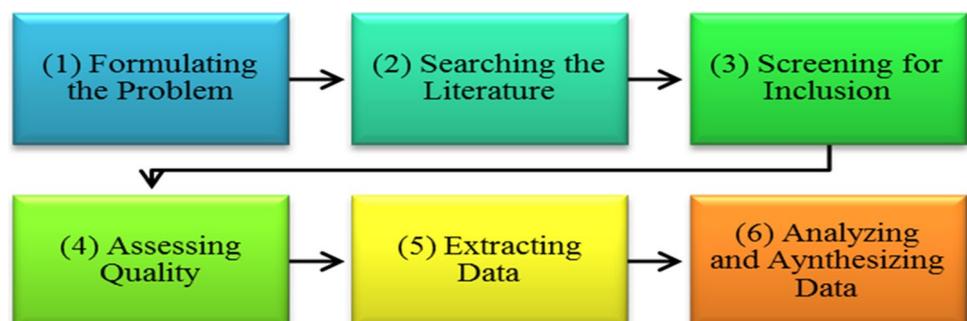
3.3 Searching the Literature

To gather the samples of published and unpublished papers, we adopted a four-step approach. First, we conducted an extensive search in all major electronic databases, including Web of Science, Science Direct, Emerald, EBSCO-Host, IEEE Xplore, Sage, JStor, Wiley Online Library, and Scopus, as well as alternative online databases, including AIS Electronic Library, ProQuest Dissertation, and Theses, SSRN and Hindawi. Second, we used Boolean combinations and variations of keywords such as “Theory of Planned Behavior,” “TPB,” “social commerce,” “s-commerce,” and “social commerce intention.” Explicitly, we used the search string “Theory of Planned Behavior” or “TPB” or “Social Commerce” or “s-commerce” or “social commerce intention.” Third, we expanded our search by carefully searching the reference lists of the related articles for other additional journal articles, working papers, conference papers, etc. (Venkatesh et al., 2016). Finally, we performed an unstructured search using the World Wide Web, such as Google and Google Scholar, for other potential books, book chapters, conference proceedings, etc. The initial search yielded a list of 2,864 articles for further screening.

3.4 Screening (Inclusion & Exclusion Criteria) and Assessing Quality

The articles identified through the initial search were subjected to further screening and filtering using precisely defined inclusion and exclusion criteria. Namely, to be considered for further analysis, the article (1) must pertain to empirical or quantitative research and not conceptual study, (2) must be written in English, (3) must contain at least one relationship from TPB, (4) must report the full correlation coefficients matrix of the constructs in TPB, (5) must report the sample size used in the study, and (6) must have an independent dataset (thus, articles that contain the same dataset were excluded to avoid bias caused by multiple counting).

Fig. 3 The six-step data gathering framework



As a result of the screening and filtering process, 2,631 unrelated articles were removed, leaving 233 articles for further assessment. However, as 211 articles were excluded due to insufficient data, 22 studies were retained for meta-analysis (Appendix Table 12). We did not include papers that were based solely on related theories such as TRA because the perceived behavior control was not evaluated in such cases. Nonetheless, papers using both TRA and TPB as their theoretical foundations were not excluded. This sample size is also similar to that (23) analyzed by Patil et al. (2018) to synthesize the factors that influence consumers' attitudes, intentions, and usage of digital payment, or adopted Montazemi and Qahri-Saremi (2015) who used 29 articles for their MASEM analysis on factors that affect the adoption of online banking. It is also similar to other meta-analyses in which 10 (Guo et al., 2016), 22 (Ma & Atkin, 2017), 25 (Kim et al., 2019), 26 (Nguyen et al., 2019), and 31 (Liu et al., 2018; Montazemi et al., 2012; Zaremohzzabieh et al., 2019) articles were examined. We then formally assessed each included study's quality.

3.5 Extracting and Coding Data

The sample for this meta-analysis included 22 studies conducted in 10 countries with 7,950 observations on 7 relationships. All articles were carefully reviewed to obtain sample sizes, reliabilities, correlation coefficients, and regression coefficients. We also documented the article author(s), title, year of publication, means, standard deviations, country, culture, type of document, and the type of statistical analysis (Jeyaraj, 2022a).

3.6 Analysis and Synthesis of Data (Effect Sizes, Standard Deviation, and Sample Size)

To perform SEM analysis in the second stage of the MASEM, we needed to pool the effect sizes of all the relationships in TPB (Dwivedi et al., 2019, 2021; Hooda et al., 2022; Tamilmani et al., 2021a). For this purpose, we adopted a random effect meta-analysis model using Meta Essentials to obtain "the zero-order correlations corrected for sampling error for the required effects averaged across the sample of studies" (Hagger et al., 2018, p. 12). The overall effect sizes were then arranged in a pooled correlation matrix which served as input for the SEM analysis (Jeyaraj, 2022b).

Moreover, as SEM can only be applied to a single sample while meta-analysis produces a sample size for every association, a pooled sample size needs to be calculated either by adopting the minimum, the average, or the harmonic mean sample size (Dwivedi et al., 2019). In this study, we calculated the harmonic mean sample size to be used for the SEM analysis. In addition, prior to SEM adoption, the standard deviations of the variables in the model need to be

established; thus, we calculated the pooled standard deviation for every variable adopted in the studies included in the meta-analysis (Dwivedi et al., 2019).

4 Results

4.1 Descriptive Statistics

The filtering process yielded 22 articles that were published between 2013 and 2019 (Appendix Fig. 6). As can be seen, there is an upward trend in the number of articles, indicating that s-commerce is becoming increasingly popular research topic.

In terms of the country in which research is conducted (Appendix Fig. 6), the highest number of s-commerce studies has been performed in Spain, followed by Asian countries (i.e., Taiwan, South Korea, and Malaysia), the UK, the U.S., and China (each with two articles only) and finally Turkey, South Africa, and Bangladesh (with just one article). Clearly, the studies included in our meta-analysis are scattered across several continents (Appendix Fig. 9).

In terms of statistical analysis (Appendix Fig. 6), in most cases, the researchers used SEM followed by multiple linear regressions (MLR), while very few used other statistical analyses such as Logit, Ordinary Linear Regression (OLR), and Correlation Analysis.

4.2 Reliability Analysis

Construct reliability refers to the consistency and stability of the construct in the measurement model and is typically evaluated via Cronbach's alpha (Hew et al., 2016; Leong et al., 2019a), composite reliability, or rho_A (Leong et al., 2019b, 2020a). A construct with a reliability index exceeding 0.70 is considered highly reliable (Hew & Sharifah, 2017) while a value between 0.35 and 0.70 signals moderate reliability (Leong et al., 2020b), and that below 0.35 is associated with low reliability (Wong et al., 2014, 2015). Table 1 demonstrates that the mean reliability of every TPB construct is above 0.70, indicating a high degree of construct reliability.

4.3 Weight Analysis

The regression coefficients of the paths between the TPB constructs are shown in Table 2. A weighted analysis entails the evaluation of the predictive power of each independent variable by calculating the frequency of significant paths related to a predictor variable and dividing it with the total number of studies that report such paths (Rana et al., 2015). A 100% weight means that the relationship is significant across all studies while a weight of 0% means that the relationship is insignificant across all studies (Ismagilova et al.,

2020). As shown in Table 3, only the BI – UB relationship is significant across all studies followed by PBC – BI (91.67%), SN – BI (88.24%), and AT – BI (86.67%).

4.4 Correlational Meta-analysis

When performing a meta-analysis, the sample size and correlation coefficient of the relationship that is identified in at least three extracted articles are required as input at the minimum (Zhao et al., 2018, 2021). We used a random-effect model to analyze and interpret correlations by presuming that the effects from each study in the sample are very similar. However, this does not mean that the sizes are all equal (Ambalov, 2018; Leong et al., 2021a). The lower (LL) and upper (UL) limits of the 95% confidence interval (CI) were thus utilized to evaluate the significance of the overall effect size. Specifically, if the interval between LL and UL included zero, we interpreted this to indicate that

the correlation is insignificant at $p < 0.05$ (Rana et al., 2015). Table 3 shows that all correlations between the TPB constructs are significant. The correlation between attitude and intention is the strongest ($r = 0.55$) followed by PBC – BI and SN – BI with the same effect size ($r = 0.50$). The weakest correlation was found between intention and use behavior ($r = 0.46$). To graphically illustrate the meta-analysis results, a forest plot was used, as the horizontal axis represents the overall effect size and a bullet represents the effect size of a particular correlation, while a whisker line extending from the bullet represents the 95% CI for that particular correlation. If all CIs are on the positive side of the horizontal axis, the correlation is significant, whereas CIs that include zero suggest that the correlation is insignificant. Based on the CIs presented in Table 3, it is evident that the traditional TPB is valid as a baseline model, and hypothesis H1 is thus supported. Appendix Fig. 7 shows the forest plots for all TPB constructs.

Table 1 Reliability analysis

| Variable | k | Minimum | Maximum | Mean | Variance |
|------------------------------|----|---------|---------|-------|----------|
| Attitude | 17 | 0.693 | 0.980 | 0.864 | 0.008 |
| Perceived Behavioral Control | 14 | 0.500 | 0.940 | 0.812 | 0.017 |
| Subjective Norm | 19 | 0.623 | 0.960 | 0.872 | 0.008 |
| Behavioral Intention | 20 | 0.630 | 0.970 | 0.875 | 0.009 |
| Use Behavior | 4 | 0.740 | 0.744 | 0.742 | 0.000 |

k = Number of studies

Table 2 Regression path analysis

| Path | k | beta coefficient | | significant | | % of sig. path | sample size | | n | average sample size |
|-----------------------------|----|------------------|-------|-------------|-----|----------------|-------------|-------|------|---------------------|
| | | lower | upper | sig | n.s | | lower | upper | | |
| Attitude → Intention | 15 | -0.080 | 0.803 | 13 | 2 | 86.67% | 143 | 1809 | 7265 | 484 |
| PBC → Intention | 12 | 0.116 | 0.809 | 11 | 1 | 91.67% | 143 | 1003 | 4920 | 410 |
| Subjective Norm → Intention | 17 | 0.015 | 0.972 | 15 | 2 | 88.24% | 75 | 1003 | 5691 | 356 |
| Intention → Use Behavior | 8 | 0.210 | 0.833 | 8 | 0 | 100.00% | 143 | 1809 | 3448 | 431 |

k = Number of studies; PBC Perceived behavioral control; sig. Significant; n.s. Not significant; n = Total sample size

Table 3 Meta-analysis of correlations between independent and dependent variables

| Correlation | r | CI 95% | | Z | p-value | Heterogeneity | | | Publication Bias | |
|--------------------------|------|--------|------|------|---------|----------------|--------|----------------|-------------------------------|--------|
| | | LL | UL | | | I ² | Q | χ ² | Fail-Safe N _(0.05) | |
| | | | | | | | | | Rosenthal | Fisher |
| AT ↔ Intention | 0.55 | 0.36 | 0.70 | 5.59 | 0.000* | 97.28% | 404.02 | 23.68 | 6228 | 12,727 |
| PBC ↔ Intention | 0.50 | 0.30 | 0.65 | 5.12 | 0.000* | 96.60% | 323.31 | 18.31 | 4231 | 7313 |
| SN ↔ Intention | 0.50 | 0.32 | 0.64 | 5.56 | 0.000* | 96.54% | 346.59 | 25.00 | 4452 | 5994 |
| Intention ↔ Use Behavior | 0.46 | 0.27 | 0.62 | 4.78 | 0.000* | 97.21% | 429.54 | 14.07 | 3203 | 3238 |

* $p < 0.001$, ^{ns} Not significant; AT Attitude; PBC Perceived behavioral control; SN Subjective norm; r Overall effect size; CI Confidence interval; LL Lower limit; UL Upper limit; Z Z-statistics; Q Cochran's Q-statistics; χ² Critical chi-square value at significance level of 0.05 and k-1 degree of freedom

4.5 Heterogeneity

Hamari and Keronen (2017) opined that, although the random-effects model is preferable in comparison to the fixed-effects model in synthesizing the effect sizes obtained in independent research studies, we conducted heterogeneity tests to further verify our random-effects model. We examined Cochran's Q -statistics and I^2 because Q -statistics is the standard test for heterogeneity while I^2 can measure the percentage of variance explained by the heterogeneity, whereby a zero percent will confirm that all variations are due to sampling errors (Dwivedi et al., 2020). Table 3 shows that all Q -statistics are indeed significant, as they considerably exceed the critical Chi-squared statistics, χ^2 (Zhang et al., 2012). Therefore, we concluded that the random effect model is a suitable model for meta-analysis.

4.6 Publication Bias

Researchers often face difficulty, as published articles tend to be biased towards reporting only positive outcomes and ignore insignificant findings, giving rise to publication bias (Zhao et al., 2018). To deal with this problem, we tested the "file drawer problem" by examining the Fail-safe N (Jeyaraj & Dwivedi, 2020), which is the number of studies that report insignificant findings that need to be added to the extracted sample to reverse the inference that there is a significant effect (Ambalov, 2018). Moreover, Rosenthal (1979) opined that a Fail-safe N exceeding the number of studies by fivefold would provide strong support for the robustness of the significant effects. Table 3 shows that Rosenthal's and Fisher's Fail-safe N values for all correlations are considerably greater than the recommended $5 \times$ sample size.

Therefore, we concluded that there is no publication bias in the meta-analysis.

4.7 Subgroup Analysis

Since I^2 statistics showed large percentages of variances explained in the effect sizes, we concluded that the variations are due to factors other than sampling errors (Kates et al., 2018). However, as heterogeneity exists in the data, there was a need to test for moderating effects and conduct subgroup analyses. Following Zhang et al. (2012), further subgroup analyses on the moderating effect of Eastern and Western cultures were conducted. Table 4 shows that the Q -between statistics for homogeneity are not significant at the $p < 0.05$ level; therefore, we concluded that there is an insignificant difference between Eastern and Western cultures. Besides, the low pseudo R^2 also implies that cultural differences are not significant.

4.8 Moderator Analysis

In addition to the cultural differences, we also performed a test for the temporal moderating effect of the publication year. Following Aguinis et al. (2005), we tested the temporal moderating effect by calculating the correlation coefficients between the year of publication and the effect size. For this purpose, median-centered publication years were used as the input instead of the absolute values to enhance the meaningfulness of the intercept and the visibility of the plots (Suurmond et al., 2017). Table 5 shows that, with the exception of the correlation between behavioral intention and perceived behavioral control, all other correlations were moderated by the year of publication. However, the correlation between

Table 4 Correlation analysis for subgroups between Eastern and Western culture

| Correlation | Eastern | Western | Pseudo R^2 | Q -between | p -value |
|--------------------------------------|---------|---------|--------------|--------------|---------------------|
| AT \leftrightarrow Intention | 0.58 | 0.49 | 7.27% | 0.89 | 0.345 ^{ns} |
| PBC \leftrightarrow Intention | 0.49 | 0.47 | 0.14% | 0.02 | 0.891 ^{ns} |
| SN \leftrightarrow Intention | 0.40 | 0.60 | 14.97% | 2.14 | 0.144 ^{ns} |
| Intention \leftrightarrow Behavior | 0.39 | 0.54 | 7.27% | 0.89 | 0.345 ^{ns} |

^{ns} Not significant; *AT* Attitude; *PBC* Perceived behavioral control; *SN* Subjective norm

Table 5 Temporal moderating effect

| Correlation | B | SE | LL | UL | beta (β) | Z-statistics | p -value |
|--|-------|------|-------|------|------------------|--------------|---------------------|
| AT \leftrightarrow Intention | 0.04 | 0.01 | 0.01 | 0.06 | 0.19 | 3.32 | 0.001* |
| PBC \leftrightarrow Intention | 0.01 | 0.01 | -0.01 | 0.03 | 0.05 | 0.96 | 0.339 ^{ns} |
| SN \leftrightarrow Intention | 0.02 | 0.01 | 0.01 | 0.04 | 0.17 | 3.12 | 0.002* |
| Intention \leftrightarrow Use Behavior | -0.02 | 0.01 | -0.03 | 0.00 | -0.11 | -2.25 | 0.025** |

* $p < 0.001$, ** $p < 0.005$, *** $p < 0.01$; ^{ns} Not significant; *AT* Attitude; *PBC* Perceived behavioral control; *SN* Subjective norm; *SE* Standard error; *LL* Lower limit; *UL* Upper limit

intention and use behavior shows a downward trend over time while others show an upward trend.

Appendix Fig. 8 presents Fisher’s *r*-to-*z* transformation of the regression of correlation on the year of publication as the moderator variable (Zhao et al., 2021). Fisher’s *r*-to-*z* transformation (Bond & Richardson, 2004; Ismagilova et al., 2021) is adopted to transform the sampling distribution of Pearson’s correlation coefficient (*r*) so that it follows the normal distribution by using the expression $z = \frac{1}{2} \ln\left(\frac{1+r}{1-r}\right)$ or $z = \tanh^{-1}(r)$. For example, Pearson’s correlation coefficient $r = 0.85$ is equivalent to the Fisher’s correlation $z = 1.256$. Therefore, some of Fisher’s correlation (*z*) values are greater than 1. The horizontal *x*-axis represents the median-center year of publication while the vertical *y*-axis represents Fisher’s *z*-transformation of the Pearson’s correlation coefficient which is labeled as Correlation (*z*). The size of the dot represents the relative weight of the correlation coefficients, while the regression line gradient represents the association between the moderator (year of publication) and Correlation (*z*). A horizontal regression line with a zero gradient indicates no temporal moderation effect.

4.9 Further Moderation Analysis of Hofstede’s Cultural Dimensions

In addition to the moderation effect of the Eastern – Western culture established via subgroup analysis, we also performed a meta-regression to further examine the effects of Hofstede’s cultural dimensions by using the study as the unit of analysis and the reliability-corrected bivariate correlations as the dependent variables. Similar to Blut et al. (2021), we matched the country information reported in each article to the coded correlations with scores for each of four dominant Hofstede’s cultural dimensions based on a secondary data source. Following Samaha et al. (2014), we matched the four dominant cultural dimensions reported by Hofstede, Hofstede, and Minkov (2010)—power distance, individualism,

masculinity, and uncertainty avoidance—with the coded correlations. The ranges of these cultural dimensions for each of the relationships are shown in Table 6. In cases where we could not match the country scores, the mean country scores for each cultural dimension were used (Blut et al., 2022). Using a procedure outlined by Hedges and Ingram (2014), we regressed the Fisher *z*-transformed, reliability-adjusted correlations on the Hofstedian dimensions. To assess the moderating effects, we employed meta-regression with the study as the unit of analysis and the reliability-corrected bivariate correlations as the dependent variables (Schepers & van der Borgh, 2020). Similar to Schepers and van der Borgh (2020), the four Hofstedian dimensions were entered sequentially as predictors in weighted least squares (WLS) where we weighted each observation by the inverse of its variance ($N - 3$).

Table 7 shows the moderating effects of the Hofstedian dimensions for each of the relationships. It can be seen that the relationship between SN and BI ($\beta = -0.500, p = 0.028$) is moderated by masculinity and is weaker in high-masculinity cultures. Similarly, there is the moderating effect of uncertainty avoidance on the association between SN and BI ($\beta = -0.270, p = 0.032$) as the relationship is weaker in countries with high uncertainty avoidance index. In addition, we also found a moderating effect of masculinity on the relationship between PBC and AT ($\beta = 0.007, p = 0.020$), whereby the relationship is stronger in countries that have a high masculinity index. Likewise, uncertainty avoidance moderates the effect of PBC on AT ($\beta = 0.020, p = 0.024$) whereby the relationship is stronger in cultures with a high index in uncertainty avoidance. For the other relationships, we did not find any significant moderating effects.

4.10 Advantages of MASEM

Ordinary meta-analysis enables scholars to assimilate and consolidate research outcomes into a sole overall effect size that mirrors the size and direction of the relations between

Table 6 Range of the Hofstedian dimensions

| Relationship | Power Distance | | Individualism | | Masculinity | | Uncertainty Avoidance | |
|--------------|----------------|-----|---------------|-----|-------------|-----|-----------------------|-----|
| | Min | Max | Min | Max | Min | Max | Min | Max |
| SN → BI | 35 | 104 | 17 | 91 | 39 | 66 | 30 | 86 |
| AT → BI | 35 | 104 | 17 | 91 | 39 | 66 | 35 | 86 |
| PBC → BI | 35 | 104 | 17 | 91 | 39 | 66 | 30 | 86 |
| BI → UB | 49 | 104 | 17 | 65 | 39 | 63 | 36 | 86 |
| SN → AT | 35 | 104 | 17 | 91 | 39 | 66 | 35 | 86 |
| PBC → AT | 35 | 104 | 17 | 91 | 39 | 66 | 35 | 86 |
| SN → UB | 35 | 104 | 17 | 89 | 42 | 66 | 35 | 86 |

SN Subjective norm; AT Attitude; PBC Perceived behavioral control; BI Behavioral intention; UB Use behavior

Table 7 Moderating effects of the Hofstedian dimensions

| Relationship | Power Distance | | Individualism | | Masculinity | | Uncertainty Avoidance | |
|--------------|----------------|-----------------|---------------|-----------------|-------------|-----------------|-----------------------|-----------------|
| | β | <i>p</i> -value | β | <i>p</i> -value | β | <i>p</i> -value | β | <i>p</i> -value |
| SN → BI | -0.160 | 0.129 | -0.004 | 0.365 | -0.500 | 0.028* | -0.270 | 0.032* |
| AT → BI | -0.003 | 0.648 | -0.002 | 0.641 | -0.005 | 0.876 | -0.006 | 0.608 |
| PBC → BI | 0.011 | 0.186 | 0.003 | 0.487 | 0.034 | 0.204 | 0.016 | 0.218 |
| BI → UB | 0.010 | 0.558 | -0.002 | 0.856 | 0.056 | 0.389 | 0.022 | 0.412 |
| SN → AT | 0.076 | 0.278 | -0.330 | 0.377 | 0.470 | 0.301 | 0.164 | 0.297 |
| PBC → AT | 0.003 | 0.582 | -0.005 | 0.241 | 0.049 | 0.007** | 0.020 | 0.024* |
| SN → UB | -0.002 | 0.130 | 0.003 | 0.169 | 0.007 | 0.235 | 0.000 | 0.889 |

* $p < 0.05$, ** $p < 0.01$; *SN* Subjective norm; *AT* Attitude; *PBC* Perceived behavioral control; *BI* Behavioral intention; *UB* Use behavior

the independent and dependent variables (Bergh et al., 2016). MASEM is more powerful than ordinary meta-analysis as it provides effect sizes by controlling other constructs of the model and reveals the information on the goodness-of-fit. Furthermore, “MASEM allows researchers to draw on accumulated findings to test the explanatory value of a theoretical model against one or more competing models, thereby allowing researchers to conduct ‘horse races’ between competing frameworks that cannot be carried out by meta-analysis alone” (Bergh et al., 2016, p. 478). It can also assess intermediate mechanisms in a chain relationship and test the mediation effect. Since the mediation effect involves at least three variables, an ordinary meta-analysis that engages bivariate relationships is ill-equipped for this purpose as well as inaccurate (Bergh et al., 2016). Moreover, MASEM can assimilate bivariate associations from various primary-level studies with a distinctive statistical power advantage, as the input for MASEM is obtained from meta-analysis, which pools thousands of samples that are significantly larger than a typical SEM sample size (Crook et al., 2008). Hence, the findings from the whole field of study may be accumulated, synthesized, and verified via alternative model structures that can provide a significantly more powerful and detailed foundation for quantitative assimilation of research outcomes compared to the ordinary meta-analysis or traditional SEM.

4.11 Correlation-based MASEM with Two-stage Random Effects SEM (TSSEM)

MASEM focuses on combining and contrasting the findings of various studies to identify the patterns among the various results and sources of divergence in these results, as well as other interesting relationships (Dwivedi et al., 2019). MASEM also enables scholars to perform an even more accurate and theory-driven quantitative review with the main benefit of not requiring that all associations stated by the theory must be assessed in every study, since the

required correlations may be calculated meta-analytically. TSSEM is a method that focuses on integrating matrices of effect sizes from various investigations and uses the pooled correlation matrix to assess the relationships hypothesized by the theoretical model.

Montazemi and Qahri-Saremi (2015) asserted that TSSEM application has several benefits over a primary study, as (1) assimilation of multiple samples in TSSEM enlarges the sample size and enhances the statistical power compared to a single-sample study, (2) TSSEM can identify valid effects that research studies with moderate sample sizes are unable to identify, (3) through the accumulation of studies before model estimation, TSSEM can generate more robust model estimates with improved accuracy and reduced sampling errors, and (4) integration of meta-analysis and TSSEM can provide a more holistic scenario and accurate evaluation of the whole structural model, as a bivariate meta-analysis that ignores interdependence among measured effects will inaccurately capture the unique effect size while sampling errors in single-sample SEM analysis may be influenced by sampling error.

4.12 Preparation

In the second stage of the TSSEM, after the bivariate correlational meta-analysis, we conducted structural equation modeling (SEM) to gauge the significance and strengths of the causal relationships. Since all meta-analyses require that effect sizes throughout all primary-level research be transformed into a common standardized metric before being assimilated, correlation coefficients are more suitable than regression coefficients as the typical effect size metric (Bergh et al., 2016). To prepare for the SEM path analysis, we arranged the random effects meta-analysis correlation coefficients in a pooled correlations matrix for use in SEM.

We then ran a MASEM path analysis with Analysis of Moment Structures (Amos 23.0) using maximum likelihood estimation to evaluate the models. Similar to other MASEM

studies (Bergh et al., 2016; Dwivedi et al., 2019; Viswesvaran & Ones, 1995; Wang & Goh, 2017), we employed the harmonic mean of the sample sizes drawn from the pooled correlation matrix as the sample size for the MASEM estimation. We obtained the size of 386, which exceeds the suggested minimum sample size for multivariate SEM analysis (Hair Jr. et al., 2017). Table 8 provides the pooled correlation matrix for the TSSEM analysis.

4.13 The Competing TPB2 Model

As suggested by Bergh et al. (2016), “MASEM allows researchers to draw on accumulated findings to test the explanatory value of a theoretical model against one or more competing models, thereby allowing researchers to conduct ‘horse races’ between competing frameworks that cannot be carried out by meta-analysis alone” (p. 478). We thus adopted the approach used by Morren and Grinstein (2021) and Combs et al. (2019) in developing the competing TPB2 model. Using this approach, we further explored all the correlation matrices and managed to draw social support from the correlation matrix employed by Hajli et al. (2014) as the additional construct to further extend the TPB model. The s-commerce context-specific construct of social support was included as its correlation matrix contains the full details of the correlation coefficients on all the constructs of the TPB model, as well as the standard deviations that are required for developing the competing TPB2 model.

4.14 Integrating Social Support into the TPB

Social support is defined as “the social resources that persons perceive to be available or that are actually provided to them by non-professionals in the context of both formal support groups and information helping relationships” (Dwivedi et al., 2021, p. 3). The social support concept has its origins in the social support theory which explicates how social relationships can affect consumers’ cognitions, behaviors, and emotions (Tajvidi et al., 2021). In the s-commerce context, social support (emotional or informational) plays a pivotal role in relationship enhancements and purchase intentions because it can provide “messages that involve

emotional concerns such as caring, understanding, or empathy as well as recommendations, advice, or knowledge that could be helpful for solving problems” (Liang et al., 2011, p. 72). In s-commerce communities, consumers can interact with each other to share supportive information that can drive their intentions to conduct commercial activities, as the review-related information and affective propensities associated with a product or service are conducive for subsequent purchase decision makings (Wang et al., 2020). Because this study intends to extend the TPB model in the context of s-commerce that involves consumers’ interactions and its impacts on consumer engagements, social support is integrated into the TPB using the new endogenous mechanism, as it can be understood as the resources that provide consumers with the understanding of a product or service (Tamilmani et al., 2021b).

5 MASEM Results

5.1 Measurement Model

The measurement models were evaluated using several goodness-of-fit indices (Pal et al., 2021; Tamilmani et al., 2020). As suggested by Hair Jr. et al. (2017), Goodness-of-Fit Index (GFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), and Incremental Fit Index (IFI) should be at least 0.95 while Standardized Root Mean Square Residual (SRMR) should be less than 0.05 and root mean square error of approximation (RMSEA) less than 0.08. Like Hahn et al. (2016) and Zaremohzzabieh et al. (2019), we compared the fits of the three models. It can be seen from Table 9 that the GFI, CGI, NFI, and IFI are at least 0.90 for the three models. Likewise, the SRMR is below 0.08, denoting a good fit of the models (Chatterjee et al., 2021). Though the RMSEA is slightly above 0.08, this value is still acceptable and is smaller than those reported by Dwivedi et al. (2019). From the goodness-of-fit indices, it can be concluded that the three models provide a very high degree of fit to the data. However, the TPB2 model is superior to the TPB1 model, as most of its fit indices are larger while its SRMR and RMSEA indices are smaller than those obtained for the TPB1.

Table 8 Meta-analytic pooled correlations matrix

| Variable | 1 | 2 | 3 | 4 | 5 |
|---------------------------------|-------|-----------|-----------|-----------|----------|
| 1. Subjective norm | | 7914 (19) | 7914 (19) | 7914 (19) | 1205 (4) |
| 2. Attitude | 0.450 | | 8232 (20) | 6037 (17) | 1205 (4) |
| 3. Perceived behavioral control | 0.230 | 0.380 | | 5033 (14) | 1205 (4) |
| 4. Intention | 0.500 | 0.550 | 0.500 | | 1205 (4) |
| 5. Use Behavior | 0.277 | 0.290 | 0.097 | 0.238 | |

Pooled correlation coefficients are shown in the lower triangle and sample size (number of studies) is shown in the upper triangle

Table 9 SEM results

| Structural path | TPB | | | | TPB1 | | | | TPB2 | | | |
|-----------------------|----------|-------|-------|-----|----------|-------|-------|--------|----------|-------|--------|--------|
| | Estimate | S.E | C.R | p | Estimate | S.E | C.R | p | Estimate | S.E | C.R | p |
| BI ← SN | 0.267 | 0.038 | 7.030 | *** | 0.753 | 0.085 | 8.873 | *** | 0.753 | 0.087 | 8.635 | *** |
| BI ← AT | 0.137 | 0.020 | 6.765 | *** | 0.289 | 0.043 | 6.766 | *** | 0.290 | 0.041 | 7.019 | *** |
| BI ← PBC | 0.147 | 0.018 | 7.952 | *** | 0.267 | 0.037 | 7.191 | *** | 0.195 | 0.034 | 5.703 | *** |
| UB ← BI | 0.299 | 0.062 | 4.808 | *** | 0.137 | 0.020 | 6.765 | *** | 0.062 | 0.019 | 3.232 | 0.001 |
| | | | | | 0.147 | 0.018 | 8.148 | *** | 0.184 | 0.017 | 11.084 | *** |
| | | | | | 0.166 | 0.070 | 2.377 | 0.017* | 0.876 | 0.083 | 10.600 | *** |
| | | | | | 0.241 | 0.061 | 3.926 | *** | 0.241 | 0.064 | 3.752 | *** |
| | | | | | | | | | 0.166 | 0.070 | 2.365 | 0.018* |
| R ² for BI | 0.470 | | | | 0.244 | | | | 0.284 | | | |
| R ² for UB | 0.057 | | | | 0.426 | | | | 0.590 | | | |
| SRMR | 0.058 | | | | 0.084 | | | | 0.090 | | | |
| GFI | 0.976 | | | | 0.069 | | | | 0.058 | | | |
| CFI | 0.950 | | | | 0.969 | | | | 0.968 | | | |
| NFI | 0.944 | | | | 0.934 | | | | 0.944 | | | |
| IFI | 0.951 | | | | 0.928 | | | | 0.939 | | | |
| RMSEA | 0.136 | | | | 0.157 | | | | 0.155 | | | |

*** $p < 0.001$, ** $p < 0.05$; SN Subjective norm; AT Attitude; PBC Perceived behavioral control; SS Social support; BI Behavioral intention; UB Use behavior

In terms of statistical predictive power (R^2), our findings show that TPB2 outperformed TPB and TPB1 for attitude (AT), behavioral intention (BI), and use behavior (UB). First, TPB2 explains 28.3% of the variance in attitude while TPB1 explains 24.4%, and TPB provides no such information. However, as TPB2 explains 59.0% of the variance in behavioral intention, it is superior to TPB and TPB1 models which have 47.0% and 42.6% of variance explained respectively. The TPB2 model also emerges as a significantly better predictor for use behavior with 9% variance explained compared to 5.7% and 8.4% for TPB and TPB1. This is a 57.9% increase in predictive power compared to the TPB model. In comparison to other meta-analyses focusing on TPB, these percentages are superior, as the 59.0% variance explained in behavioral intention is significantly higher than the 31.0% obtained by Rise et al. (2010), 33.0% by Ravis et al. (2009), and 39.0% by Ravis and Sheeran (2003). However, no percentages of variance explained for use behavior are reported in the articles published by Rise et al. (2010), Ravis et al. (2009), and Ravis and Sheeran (2003).

5.2 Structural Model

The structural models were examined via bootstrapping with maximum likelihood estimation (Vimalkumar et al., 2021; Wong et al., 2022) and the findings are reported in Table 9. It is evident that all relationships in the original TPB model are significant ($p < 0.001$), whereby subjective norms ($\beta = 0.267$) are the strongest predictor of behavioral intention, followed by perceived behavioral control ($\beta = 0.147$) and attitude ($\beta = 0.137$).

On the other hand, the path analysis of the TPB2 model shows that all paths are significant and that subjective norms ($\beta = 0.195$) are the strongest predictor for behavioral intention followed by perceived behavioral control ($\beta = 0.184$) and attitude ($\beta = 0.062$). Subjective norms ($\beta = 0.241$) are also the strongest predictor of use behavior followed by behavioral intention ($\beta = 0.166$). Finally, subjective norms ($\beta = 0.753$) outperformed perceived behavioral control ($\beta = 0.290$) in predicting attitude toward s-commerce.

5.3 Mediator Analysis

In addition to the path analysis, we also examined the mediating effect or indirect effect of the mediators in the TPB, TPB1, and TPB2 models. Table 10 shows that perceived behavioral control, attitude, and subjective norms have partial complementary mediating effects on use behavior. Similarly, there are also partial complementary mediating effects of subjective norms and perceived behavioral control on behavioral intention. Overall, as further paths are added to the TPB1 model, these mediating effects become weaker.

Table 10 Standardized Indirect Effects

| Exogenous variable | Endogenous variable | TPB | TPB1 | TPB2 |
|--------------------|---------------------|-------|-------|-------|
| SN | BI | | 0.104 | 0.047 |
| PBC | BI | | 0.040 | 0.018 |
| PBC | UB | 0.044 | 0.031 | 0.034 |
| AT | UB | 0.041 | 0.023 | 0.010 |
| SN | UB | 0.080 | 0.062 | 0.040 |
| SS | UB | | | 0.146 |

SN Subjective norm; AT Attitude; PBC Perceived behavioral control; SS Social support; BI Behavioral intention; UB Use behavior

6 Discussion

The aim of the present study was to assess the effects of TPB constructs on consumers' intentions and use behavior in the s-commerce context. For this purpose, we critically reviewed the TPB model and recommended a new TPB2 model by testing the competitive models using random effect two-staged meta-analytic structural equation modeling (TSSEM) analysis. Our findings provide several interesting and important insights for scholars and practitioners, as they offer empirical support for all the relationships in TPB and TPB2 models. Thus, our investigation has clarified the inconsistencies of the findings in existing studies, as it shows that they are not caused by the TPB theory itself but are rather due to differences in samples and national cultures. Moreover, our work shows that the proposed TPB2 model has outperformed the original TPB model in predicting consumers' intention and use behavior in s-commerce. The proposed TPB2 model has added extra value to s-commerce scholarship in terms of the explanatory power and parsimony, and it may help authors of future studies to further enhance the predictive power of the original TPB model while providing greater interpretability of the findings yielded.

6.1 Implications for Theory

There are several important theoretical implications of our work. First, using the internal mechanism (Tamilmani et al., 2021b), we proposed and successfully validated the TPB2 model with the addition of the new paths, namely $SN \rightarrow AT$, $SN \rightarrow UB$, and $PBC \rightarrow AT$. In addition, using the new exogenous mechanism (Tamilmani et al., 2021b), social support was included as an s-commerce context-specific construct to strengthen the research model. With the application of the new moderation mechanism (Tamilmani et al., 2021b), masculinity and uncertainty avoidance were included as the moderating variables. This enhancement has improved the original TPB model by increasing the interpretability as well as the percentage of variance explained. Instead of

adding too many constructs to complicate the model, we have enhanced the novelty and relevance without losing the parsimony of the TPB2 model. Unlike the TPB, in TPB2, the three core variables (SN, PBC, and AT) are not independent. In other words, consumers' attitudes towards s-commerce rely on the effects of social interactions and WoM on SN and PBC. Besides, we have confirmed that subjective norms have a direct impact on use behavior in social commerce, which is highly relevant given that TPB posit no effect of SN on UB, and this has been falsified in TPB2. The immense social interactions and UGC in s-commerce have enhanced the effect of SN not only on BI but also on consumers' use behavior. In addition, due to the increase in social interactions in s-commerce, the effect of BI on UB has decreased while the effect of SN on UB has increased. Moreover, with the increase in social interactions in s-commerce, the effect of AT on BI has decreased while the effect of PBC on BI has increased. Overall, TPB2 exhibits enhancements in predictive power in terms of the percentage of variance explained for AT, BI and UB due to the increase in social interactions. Hence, TPB2 can better capture the nature of s-commerce in terms of social interactions, WoM, and UGC.

Second, as a part of the present study, we empirically and statistically validated the significance of all paths in the original TPB model and further verified the effect of TPB in predicting consumers' intentions and use behaviors. This is important, as existing studies have yielded mixed and inconsistent findings, leading to differences in inferences and interpretations among scholars and researchers. Via TSSEM – MASEM analysis, better and clearer understandings have been obtained to address the issues of mixed, scattered, and inconsistent findings.

Third, the findings obtained in this study verified the order of importance among the predictors of behavioral intention in the TPB model. The authors of existing studies have reported mixed order of importance, leading to the lack of agreement on the most important construct in TPB. In addressing this issue, we successfully established the order of importance of the TPB constructs in a holistic way, allowing priority to be given to the most important factors, followed by the less important ones.

Regarding the effect of cultural differences on the TPB model, we found no evidence supporting such effect between the Eastern and Western societies. Our findings show that TPB has cultural invariance, and this can be explained by the popularity of s-commerce and its nature. With the proliferation of social interactions, WoM, and UGC, we anticipate that cultures will have an immaterial effect on TPB. This discovery has provided empirical evidence to support the robustness of the TPB model across different cultures. It further shows that TPB remains solid and sound against cultural differences. The cultural invariance of TPB enables s-commerce vendors to engage the same business strategies

globally. It also indicates that, even under the strong influence of social interactions in s-commerce, the TPB is resilient against such impact and can sustain its cultural invariance.

Though there are no cultural differences between East and West, based on the more specific further moderation analysis of the dominant Hofstedeian cultural dimensions, we found that masculinity and uncertainty avoidance are the most influential Hofstedeian cultural dimensions, as they demonstrate significant moderating effects on the SN – BI and PBC – AT relationships. However, there are no significant moderating effects of the power distance and individualism on other relationships. With this national culture analysis, our work has provided a more specific contextualization of the TPB2 model compared to the basic TPB model. Even though there were calls to examine the boundaries of this theory from the cultural perspective, not many studies have been done as a result (e.g., Blut et al., 2022). This study is thus particularly valuable, as it provides empirical evidence to support the moderating effects of masculinity and uncertainty avoidance on the TPB2 model that can serve as a foundation for future investigations.

Furthermore, we also found temporal moderating effects of the time lag in terms of years of publication. Except for the association between behavioral intention and use behavior which has a slightly downward trend, all other relationships show an upward trend. The decrease in the effect of BI on UB is caused by the mature social interactions in s-commerce where consumers' actual use behaviors are mostly driven by their social interactions rather than their behavioral intentions. The effect sizes between attitude and intention, as well as subjective norms and intention, increase with the year of publication. This finding indicates that the links between these constructs are strengthening over time. This phenomenon occurs due to the rise of social interactions in s-commerce where consumers' attitudes become an important driver for their behavioral intentions, as their attitudes are greatly influenced by the prevalence of social interactions. Likewise, the proliferation of social interactions in s-commerce has also caused social norms to be a major contributor to consumers' behavioral intentions. This is expected, given that social interactions provide strong social influence in inculcating social norms that eventually affect users' behavioral intentions.

However, the link between behavioral intention and use behavior decreases slightly over time. This phenomenon is explained by the prominent effect of social interactions in s-commerce that surpasses the effect of behavioral intention on use behavior. Instead, social interactions have led to a direct effect of social norms on use behavior, as consumers' use behaviors are now mostly driven by social influence rather than their intentions to use. We also found partial complementary mediation effects of the mediator variables

in the original TPB and the proposed TPB2 model. Specifically, the original TPB model portrays behavioral intention as the only mediating variable; however, in the TPB2 model, attitude and behavior intention also act as mediators. This phenomenon occurs as a result of the rise of social interactions in s-commerce that has affected consumers' attitudes and behavioral intentions. This is a new horizon that has not been uncovered in existing studies and can further extend the extant TPB and s-commerce literature.

Next, as indicated by the results yielded by the MASEM analysis of the two models, our work has successfully validated the TPB2 model. The empirically validated new relationships of $SN \rightarrow AT$, $PBC \rightarrow AT$, and $SN \rightarrow UB$ will thus serve as an eye-opener to researchers and scholars, as previously there have been no studies that revealed such relationships. These empirically validated new relationships are vital not only for the s-commerce field but also for other research domains because, with the newly developed relationships, researchers and practitioners can gain new knowledge and understanding of the untapped paths that have been overlooked in the extant literature. The newly developed relationships will also serve as a theoretical foundation for its application in other research contexts while advancing the literature on s-commerce beyond the existing TPB model.

Finally, with the addition of the new paths in the TPB2 model, we discovered that the indirect effects of PBC, AT, and ST on UB have decreased. These findings further explain the effects of social interactions in s-commerce that have changed how consumers behave compared to conventional e-commerce. They indicate that the TPB2 constructs' direct effects on UB are more significant than their indirect effects. Besides, we also found new indirect effects of SN and PBC on BI, which were overlooked in the TPB model. Hence, TPB2 can provide a greater understanding of consumers' BI and UB compared to TPB.

6.2 Implications for Practice

Our findings show that subjective norms play a vital role in affecting attitude, behavioral intention, and use behavior in s-commerce. Hence, s-commerce service vendors may take into consideration ways and means to enhance consumers' subjective norms. For example, greater publicity via social media to highlight consumers' testimonials on their experiences, as well as success stories in using the s-commerce platforms, can be used to strengthen the subjective norms related to s-commerce utilization. Similarly, s-commerce service providers may consider ways to enhance the subjective norms pertaining to s-commerce among consumers by providing forums and discussion groups within the s-commerce platforms so that consumers may sense the existence of subjective norms in the virtual communities. Managers and policymakers may also take a proactive stance

in promoting social influence by sharing information to generate positive eWoM while adopting appropriate countermeasures to nullify negative comments or feedback.

Furthermore, since perceived behavioral control has a significant impact on attitudes and behavioral intentions related to s-commerce, it is vital for s-commerce service providers to allow consumers to have sufficient flexibility when using s-commerce platforms. For example, a variety of options can be offered for consumers to customize the s-commerce platforms according to their needs and wants, and the same should be done for the payment and delivery methods. Besides, policymakers may grant more freedom to s-commerce consumers in terms of regulatory and law enforcement so that the consumers will have more control over the usage of the s-commerce platforms.

Next, since attitude exerts a direct impact on behavioral intention and an indirect effect on use behavior in s-commerce, there is a pressing need to ensure that positive attitudes can be formed among the consumers. For this reason, s-commerce vendors should dedicate more effort and attention to creating positive attitudes among consumers. One of the approaches that they may consider relies on educating the consumers on the proper ways of using s-commerce. For example, prudence in online shopping and expenditure can be inculcated among consumers by explaining the consequences of overspending or buying unnecessary products or services. Moreover, the etiquette of using s-commerce should be introduced (e.g., by providing a "Do and don't do" list) so that consumers will have a proper attitude and would refrain from unethical behaviors while performing online shopping on the s-commerce platforms. In addition, since social support plays a pivotal role in s-commerce, s-commerce vendors and service providers can fully use this finding to strengthen the emotional and informational support among s-commerce consumers. This may be achieved by providing more opportunities for consumers to share information and experiences, while giving them greater freedom to express their views and reviews so that other consumers can benefit from these sources of information.

Finally, scholars and researchers can use the newly validated TPB2 to investigate user behaviors in new IS artifacts in various domains, especially in relation to the unforeseen and upcoming IR4 technologies. They can also extend the TPB2 based on the practical guide to further increase the parsimony and predictive power of the research model. With the more widespread application of the TPB2, additional understanding can be obtained, as the model can provide greater interpretability and explanatory power, since it was developed through a comprehensive MASEM approach. This will revitalize the popularity of the theory and will allow it to regain its dominance not only in the IS field but also in other behavioral science or design science domains.

6.3 A Practical Guide for TPB2

Based on the newly developed TPB2 model, we propose a general practical guide (Fig. 4) for the context of AI-enabled conversational commerce through the extension and incorporation of some new exogenous, moderating, contextual, and outcome mechanisms (Tamilmani et al., 2021b). Similar to Cheng (2018) and Singh (2020), some external variables can be drawn from the context of AI-driven chatbots. The extension via additional external variables to the TPB2 model is in line with the new exogenous mechanisms used by Venkatesh et al. (2016) and Tamilmani et al., (2021b). For example, special attributes of AI-driven chatbots (e.g., perceived anthropomorphism, perceived intelligence, and perceived animacy) can be incorporated into the extended TPB2 model (Balakrishnan & Dwivedi, 2021). To enhance the research model, we have suggested the new contextual mechanisms based on the study conducted by Hong et al. (2014), as these authors employed contextual variables that are specific to the context of the AI-enabled conversational commerce. For example, managerial support and technical capacity from the context of conversational commerce firm capacity can be included to increase the parsimony and predictive power. In addition, we also used the new outcome mechanisms proposed by Venkatesh et al. (2016) and Tamilmani et al. (2021b) as new outcome variables. For instance, an AI-enabled conversational commerce firm's

performance is incorporated into the TPB2 model to gain better understanding of the impacts of use behavior and to provide more benefits to practitioners.

Similar to Bu et al. (2021), control variables such as conversational commerce's firm size and annual sales can also be included. Finally, new moderating mechanisms (Tamilmani et al., 2021b; Venkatesh et al., 2016) can be applied to the TPB2 model by introducing new moderating variables to further enhance the predictive power of the model. For example, familiarity with AI-driven conversational commerce can be included as a moderating variable (Tamilmani et al., 2021b; Venkatesh et al., 2016). In the next section, we will elaborate in detail on an exemplar model of AI-enabled conversational commerce using an extended TPB2 model.

6.4 A TPB2 Exemplar Model

Similar to the approach adopted by Venkatesh et al. (2016), to provide a clearer understanding of how the practical guide can be used by scholars and researchers, we have provided an exemplary research model (Wang et al., 2020) that extends the TPB2 in the context of AI-enabled conversational commerce (AI-CC) adoption on firm performance (Fig. 5). The term conversational commerce (CC) was coined by the founder of Uber, Chris Messina in 2015 (Quoc, 2016). AI-CC refers to the applications of conversation via a chat app, a chatbot, a voice assistant, or a messaging platform to

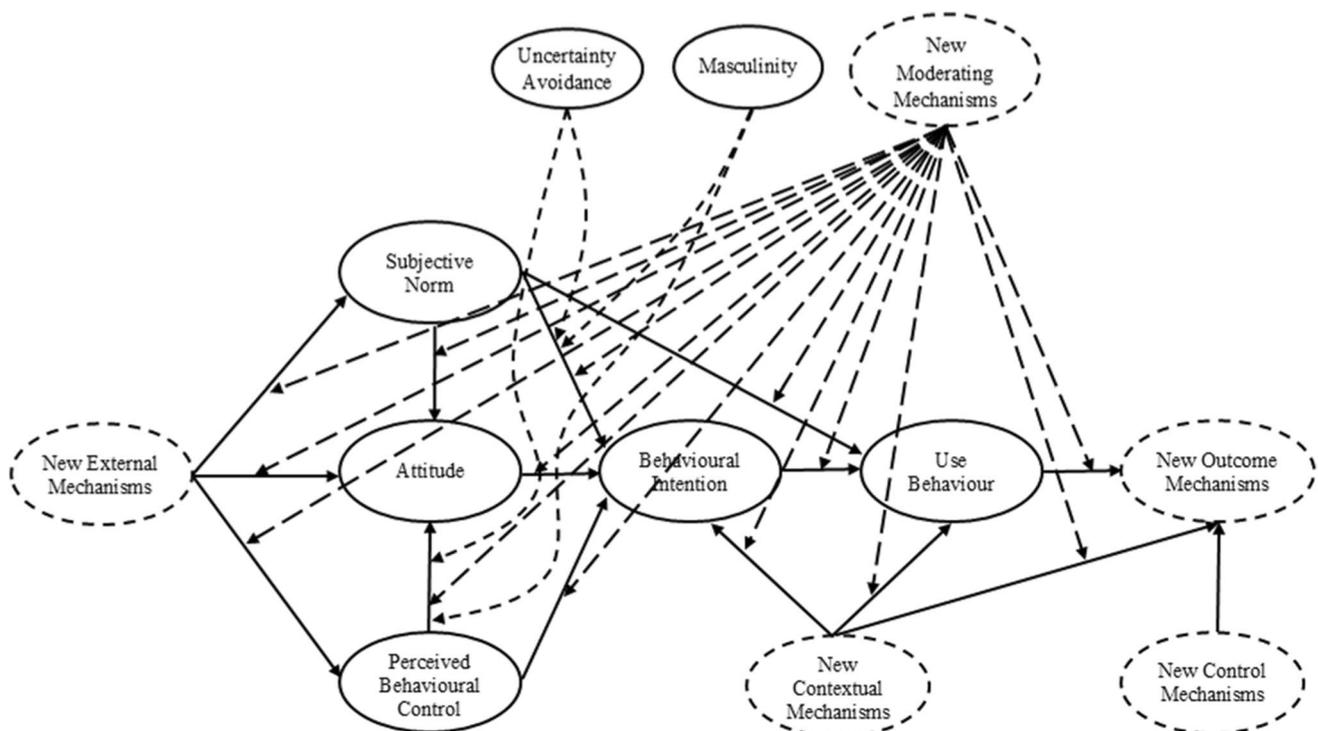


Fig. 4 A practical guide for extending the TPB2

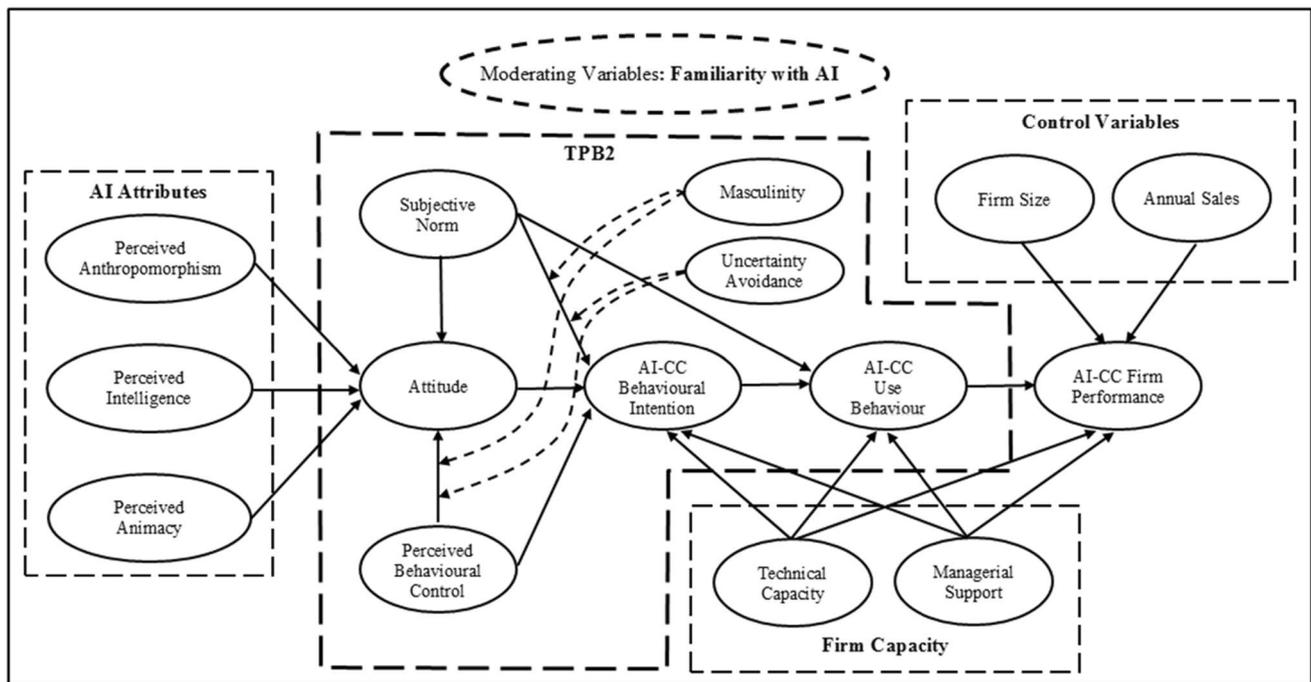


Fig. 5 An exemplary model for the context of AI-enabled conversational commerce usage and firm performance. AI-CC = AI-enabled Conversational Commerce

sell products and services (Rabassa et al., 2022). Though the term *Digital Assistant* is interchangeably used with the AI (Artificial Intelligence) agent, chatbot assistant, and voice assistant, it is an umbrella term that entails all these entities and it mainly incorporates AI-powered algorithmic chatbots, which utilize Natural Language Processing (NLP) to communicate with customers (Balakrishnan & Dwivedi, 2021). Conversational commerce bridges “the human–computer gap in online commerce by creating a humanized ecosystem where customers and technology-mediated brand representatives can chat and close deals” (Lim et al., 2022, p. 1132).

In conversational commerce, the consumer relationship and purchase journey are divided into five main phases, namely awareness, consideration, decision, retention, and advocacy. During the awareness phase, customers recognize their needs and discover the online store or offer. In the consideration phase, customers have decided on what to buy and start to seek information to find the best solution. In the decision phase, customers have obtained the information needed and will evaluate the available options based on some key criteria such as price, benefits, performance, quality, and trust in the brand. During the retention phase, customers are ready to finalize the purchase but not necessarily to cross the finish line as cart abandonment is rampant in e-commerce. Therefore, reminding the customers about the purchase with a simple text message and communicating with them will help them to cross the finish line. Marketing tactics such as coupons, discounts, and special deals may

facilitate the process. Finally, in the advocacy phase, customers have made a purchase but the journey is not over as they may experience buyers’ remorse. Therefore, instilling a sense of confidence in the brand through communication with customers will boost their satisfaction and brand loyalty. In this phase, customers become the brand ambassadors who recommend the products to their friends, family members, and colleagues.

There are four categories of conversational commerce, namely live chat, chatbots, messaging apps, and voice assistants. Live chat is the most popular omni-channel that allows customers to obtain answers instantly via retailers’ websites. Since live chat allows one agent to chat with several customers at once, it can reduce waiting time and boost customer satisfaction. Chatbots are software that assists customers in getting the answers to their questions via text messages. Chatbots can chat with many customers at once and provide the needed information within seconds. Unlike conventional apps, customers do not need to learn how to use chatbots, thus making them popular among less tech-savvy consumers. Simple queries such as case resolutions, comparable products, and order status can be automatically assigned to chatbots, and in more advanced versions, conversational AI can be used to further personalize the experience. On the other hand, messaging apps such as *WhatsApp* or Apple’s *iMessage* allow customers to exchange instant messages via private communication with the brands. They also allow the use of memes, videos, emojis, and GIFs to boost customer

engagement in a much more natural and personal communication. Finally, voice assistants such as *Alexa*, *Cortana*, *Siri*, and *Google Assistant* are software applications that are activated via voice commands. Customers like them for their convenience, multi-tasking capacity, and fun features. Owing to the power of artificial intelligence, machine learning, and natural language processing, voice assistants can learn about customers' specific preferences and suggest solutions that match their track records. This has enabled marketers to create personalized voice ads and establish stronger bonds with customers.

Therefore, based on the four categories of conversational commerce, we may differentiate two broad spectra of conversational commerce, namely the AI-enabled and non-AI-enabled conversational commerce. Voice assistants such as Amazon's *Alexa*, Apple's *Siri*, Microsoft's *Cortana*, and *Google Assistant* are examples of AI-enabled conversational commerce. Likewise, conversational AI chatbots such as *H&M*, *Slush*, *Vainu*, *Sephora*, *Babylon Health*, and *CNN chatbots* are also examples of AI-enabled conversational commerce. On the other hand, messaging apps such as live chats such as *Facebook Messenger*, *WhatsApp*, *WeChat*, *Drift*, and Apple's *iMessage* are examples of non-AI-enabled conversational commerce. Similarly, live chat agents such as "connect with a specialist" in Apple's online store, etc., are considered non-AI-enabled conversational commerce tools.

In this conversational commerce exemplary model, perceived anthropomorphism, perceived intelligence, and perceived animacy were integrated into the TPB2 model as the external variables (Balakrishnan & Dwivedi, 2021). Anthropomorphism entails both software and hardware features that assign human-like attributes to a non-human agent. The anthropomorphism in chatbots can build a stronger brand attitude and purchase intention. Due to AI's cognitive and reasoning capacity, intelligence has been an imperative attribute of AI-enabled systems. Retail operations and personalized customer service can be enhanced by machine intelligence. When humans are strongly attached to a machine, they personify it to a certain level, and even though it is not perceived as a living thing, it can animate to a certain level and this phenomenon is known as perceived animacy. It is defined as believing machines as living things that can move and interact. To create an animatic environment, developers of digital assistants use multi-functional AI attributes with embedded human features. For instance, *Alexa* can mimic human-like voices with intelligent algorithms to resemble a human – human experience instead of a human – machine experience. Hence, we anticipate that perceived animacy, intelligence, and anthropomorphism will have a significant influence on customer attitudes as the technology advances in the future.

In the AI context, commitment from managers is a vital factor for organizational change, as well as IS and IT implementation, and must be consistent and constant to ensure that the project does not fail due to the lack of alignment between project goals and organizational mission and vision (Chen et al., 2021). On the other hand, the technical capability is the physical asset that is important for innovation adoption and represents the collective resources of the organizations that can be deployed in providing the flexibilities and scalabilities for organizational operations. Thus, technical capability is the main factor that affects IT adoption, as organizations that can deliver technical solutions effectively and integrate the AI technologies will be successful in adopting the AI applications (Chen et al., 2021). Therefore, managerial support and technical capability are integrated into the TPB2 as the contextual variables pertaining to firm capacity.

Similar to Chen et al. (2021), firm size and annual sales are included as the control variables, as both can influence the variance in the decision of AI adoption which affects firm performance. Finally, the adoption of AI-enabled s-commerce will have significant effects on firm performance as it can enhance the effectiveness of strategies focusing on customers, users, and external market knowledge creation (Bag et al., 2021). Therefore, s-commerce firm performance is included as the outcome variable. Due to the differences in the level of familiarity with AI, it is anticipated that users with a high level of familiarity will value the AI technologies in a more positive way, and will consequently have better attitudes toward them as they have more knowledge about the usefulness and practical value of the AI technologies compared to users with a low level of familiarity (Belanche et al., 2019). Therefore, familiarity with AI is included as the moderating variable.

6.5 Research Agenda for TPB2

Besides the newly developed TPB2 model and the practical guide, we propose the following research agenda:

1. To extend the theoretically meaningful predictors (e.g., compulsive/impulsive behavior, time-pressure, loneliness/companionship, personality traits/experience/lifestyle/habits, financial situation, etc.)
2. To expand the levels of the predictors (e.g., individual, dyad, team, group, manufacturer, supplier, advertiser, marketer, vendor, etc.)
3. To examine the linear, nonlinear, or curvilinear effects using novel statistical analyses, such as artificial neural network, necessary condition analysis (NCA), fuzzy-set comparative qualitative analysis (*f*s-QCA), multi-level

modeling, latent growth modeling, data mining, machine learning, predictive analytic, big data analytic, etc.

4. To diversify the research methodologies (e.g., experimental, longitudinal, mixed-methods, action research, case studies, observations, grounded theory, comparative study, etc.)
5. To integrate the TPB2 model with other research frameworks (e.g., technology-organization-environment (T-O-E), task-technology-fit (T-T-F), stimulus-organism-response (S-O-R), etc.)
6. To examine the temporal effects in TPB2 (e.g., pre-adopter, adopter, post-adopter, experienced/non-experienced)
7. To expand the range of moderators and mediators (e.g., cross-national differences, types of platforms, customer/product/brand/service/system attributes, religion/ethnicity/linguistic diversity, digital divide/disparity, usage frequency, actual spending, promotion/incentive, social status, etc.)

7 Limitations and Future Research Directions

Like other meta-analysis studies (Ambalov, 2018; Dwivedi et al., 2019; Zaremohzzabieh et al., 2019), this work was motivated by the view that it is worth synthesizing findings from a collection of constructs and measures drawn from a large sample of related investigations. However, caution should be taken when interpreting the findings reported here, as several limitations need to be considered. First, only articles in which Pearson's correlation coefficients were reported were examined. However, authors of some studies may have reported only linear regression or structural equation modeling path coefficients, which were not included in the study. Second, some authors did not report the required statistics, such as sample size, mean, standard deviation, and reliability. As the MASEM requires these statistics, we discarded all articles in which these values were not available, and this restriction may partially affect our MASEM results. Third, in this study, we only considered articles written in English, thus neglecting potentially valuable results reported in other languages. Nevertheless, the effect of the excluded studies has been addressed by using the Fail-safe N approach which indicates that a very large number of studies are needed to overturn the significance of a relationship. As a recommendation, authors of future studies may expand the scope of the meta-analysis to include articles written in other languages. Fourth, in this study, we only assessed the moderating effect of cultural differences and year of publication. Hence, in future studies, other moderators such as demographic variables (i.e., gender, age, education, etc.)

should also be considered. Fifth, we only examined the basic constructs of TPB, and this has limited the predictive power. As such, the research framework adopted in future studies may include additional theories or variables to enhance the predictive power. Sixth, the current study focused solely on the traditional individual planned behavior. As group discussion is one of the key aspects of social media usage, in future studies, it would be beneficial to also examine how the TPB2 model can be used to investigate the effects of "group planned behaviors" such as group buying, group traveling, group financing, and so on. Seventh, with the emergence of some innovative business models such as online-to-offline (O2O), peer-to-peer (P2P), consumer-to-consumer (C2C), factory-to-consumer (F2C), etc., it would be interesting to examine the effectiveness of the TPB2 model based on these innovative s-commerce models. Also, the TPB2 model can also be used to examine the emerging phenomenon of the 'Metaverse' (Dwivedi et al., 2022a) and adoption of digital technologies for climate change (Dwivedi et al., 2022b). Eighth, the generalizations that can be drawn from the present study are limited to the s-commerce context. Therefore, it is recommended that TPB2 is adopted in other research contexts. Finally, as recommendation systems and social network analytics are increasingly popular in social commerce, we suggest that the effect of these intelligent technologies on the applicability and validity of existing behavior models such as TPB and the newly proposed TPB2 be examined. We further advise exploring whether recommendations in social media may have effects that are different from human recommendations regarding attitude, user intention, and behavior. So far, we have not found many insightful reports on this issue, which indicates that this is a very promising new research direction.

8 Conclusion

The work performed as a part of the present study has verified the effect of TPB in predicting consumers' intentions and use behaviors in the s-commerce context. In this article, we revisited and reassessed the original TPB model and introduced a new TPB2 model for future studies. The study findings show that TPB2 outperforms TPB in terms of interpretability and predictive power. We also examined the role of cultural differences as well as the moderating effect of year of publication. The effects of the mediators in the two models were also assessed. Generally, the outcomes of this study have provided a vital and novel theoretical understanding of the s-commerce literature.

Appendix 1

Table 11 Summary of s-commerce studies that applied TPB

| No | Author(s) | Year | AT-BI | PBC-BI | SN-BI | BI-UB |
|----|-----------------------------------|------|----------------------|--------|---------------------|--------|
| 1 | (Akman, 2014) | 2014 | | | 0.225* | 0.733* |
| 2 | (Bojei & Abu, 2016) | 2019 | 0.803* | 0.809* | 0.643* | |
| 3 | (Ghosh, 2019) | 2017 | 0.220* | | | |
| 4 | (Hajli et al., 2015) | 2014 | 0.420* | 0.150* | 0.490* | 0.380* |
| 5 | (Hansen et al., 2018) | 2017 | -0.080 ^{ns} | 0.150* | | |
| 6 | (Ho & Rezaei, 2018) | 2018 | 0.092 ^{ns} | 0.116* | 0.467* | |
| 7 | (Hong et al., 2019) | 2018 | | | 0.308* | |
| 8 | (Hung et al., 2018) | 2018 | 0.495* | 0.233* | 0.072 ^{ns} | |
| 9 | (Ko, 2017) | 2017 | | 0.730* | | |
| 10 | (Liébana-Cabanillas et al., 2014) | 2014 | 0.160* | | 0.460* | |
| 11 | (Liébana-Cabanillas et al., 2018) | 2019 | | | 0.374* | |
| 12 | (Lin & Wu, 2015) | 2015 | 0.388* | 0.264* | 0.217* | 0.244* |
| 13 | (McLaughlin & Stephens, 2019) | 2019 | 0.280* | 0.170* | 0.360* | |
| 14 | (Pujadas-Hostench et al., 2019b) | 2019 | 0.400* | 0.400* | 0.100* | 0.640* |
| 15 | (Pujadas-Hostench et al., 2019a) | 2019 | 0.251* | 0.219* | 0.015 ^{ns} | 0.327* |
| 16 | (Qin et al., 2018) | 2016 | | | 0.348* | |
| 17 | (Sanne & Wiese, 2018) | 2018 | 0.706* | | 0.143* | 0.822* |
| 18 | (Shim & Altmann, 2016) | 2016 | | | | |
| 19 | (Shin, 2013) | 2013 | 0.230* | | 0.430* | 0.210* |
| 20 | (Smith et al., 2013) | 2013 | 0.760* | 0.740* | 0.820* | |
| 21 | (Yeon et al., 2019) | 2019 | 0.423* | | | 0.833* |
| 22 | (Zhang & Wang, 2019) | 2019 | | | 0.286* | |
| | Smallest beta value | | -0.080 | 0.116 | 0.015 | 0.210 |
| | Largest beta value | | 0.803 | 0.809 | 0.820 | 0.833 |

AT Attitude; PBC Perceived behavioral control; SN Subjective norm; BI Behavioral intention; UB Use behavior; * = significant, ^{ns} = not significant

Appendix 2

Table 12 Studies included in the Meta-analysis

| Study | Author(s) | Article Title | Year | Samples |
|-------|-----------------------------------|--|-------|---------|
| 1 | (Akman, 2014) | “Exploring the Adoption of Social Media Commerce Using Extended Theory of Planned Behavior” | 2014 | 143 |
| 2 | (Bojei & Abu, 2016) | “Intention to use Social Media Tools Among Business-To-Consumer (B2C) Practitioners in Klang Valley, Malaysia: Insight from TPB” | 2016 | 200 |
| 3 | (Ghosh, 2019) | “Exploring The Factors Influencing Millennia’s Intention-To-Purchase of Facebook Advertising in Bangladesh” | 2017 | 327 |
| 4 | (Hajli et al., 2015) | “A study on the continuance participation in on-line communities with social commerce perspective” | 2014 | 200 |
| 5 | (Hansen et al., 2018) | “Risk, Trust, and the Interaction of Perceived Ease of Use and Behavioral Control in Predicting Consumers' Use of Social Media for Transactions” | 2017 | 318 |
| 6 | (Ho & Rezaei, 2018) | “Social Media Communication and Consumers Decisions: Analysis of the Antecedents for Intended Apps Purchase” | 2018 | 230 |
| 7 | (Hong et al., 2019) | “Research on Influencing Factors of Users’ Adoption Intention of WeChat marketing” | 2018 | 273 |
| 8 | (Hung et al., 2018) | “Investigating the factors influencing small online Vendors' intention to continue engaging in social commerce” | 2018 | 166 |
| 9 | (Ko, 2017) | “Exploring the Factors that Influence Consumers’ Social Commerce Intentions on Social Networking Sites” | 2017 | 248 |
| 10 | (Liébana-Cabanillas et al., 2014) | “Mobile social commerce acceptance model: factors and influences on intention to use s-commerce” | 2014 | 353 |
| 11 | (Liébana-Cabanillas et al., 2018) | “New social consumer? Determining factors of Facebook commerce” | 2019 | 205 |
| 12 | (Lin & Wu, 2015) | “Exploring antecedents of online group-buying: Social commerce perspective” | 2015 | 202 |
| 13 | (McLaughlin & Stephens, 2019) | “The theory of planned behavior: the social media intentions of SMEs” | 2019 | 89 |
| 14 | (Pujadas-Hostench et al., 2019b) | “Clothing brand purchase intention through SNS” | 2019 | 1003 |
| 15 | (Pujadas-Hostench et al., 2019a) | “Integrating theories to predict clothing purchase on SNS” | 2019 | 150 |
| 16 | (Qin et al., 2018) | “Understanding the Intention of Using Mobile Social Networking apps” | 2016 | 151 |
| 17 | (Sanne & Wiese, 2018) | “The theory of planned behaviour and user engagement applied to Facebook advertising” | 2018 | 656 |
| 18 | (Shim & Altmann, 2016) | “How Marginally Does Impulse Buying Intention Change in Social Commerce? Nonparametric Regression Approach” | 2016 | 500 |
| 19 | (Shin, 2013) | “User experience in social commerce: in friends we trust” | 2013 | 329 |
| 20 | (Smith et al., 2013) | “Social Commerce from a Theory of Planned Behavior Paradigm: an analysis of Purchase intention” | 2013 | 75 |
| 21 | (Yeon et al., 2019) | “What creates trust and who gets loyalty in social commerce?” | 2019 | 323 |
| 22 | (Zhang & Wang, 2019) | “How online social ties and product-related factors influence purchasing intention in mobile social commerce context?” | 2019 | 1809 |
| | | | Total | 7950 |

Appendix 3

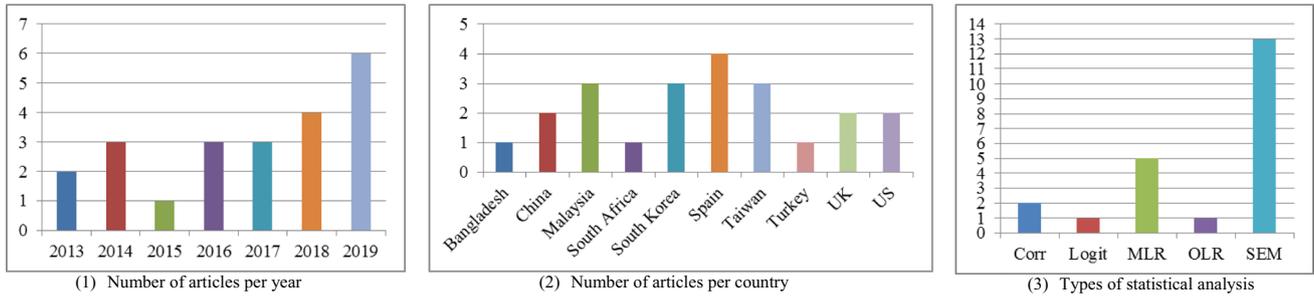


Fig. 6 Descriptive statistics

Appendix 4

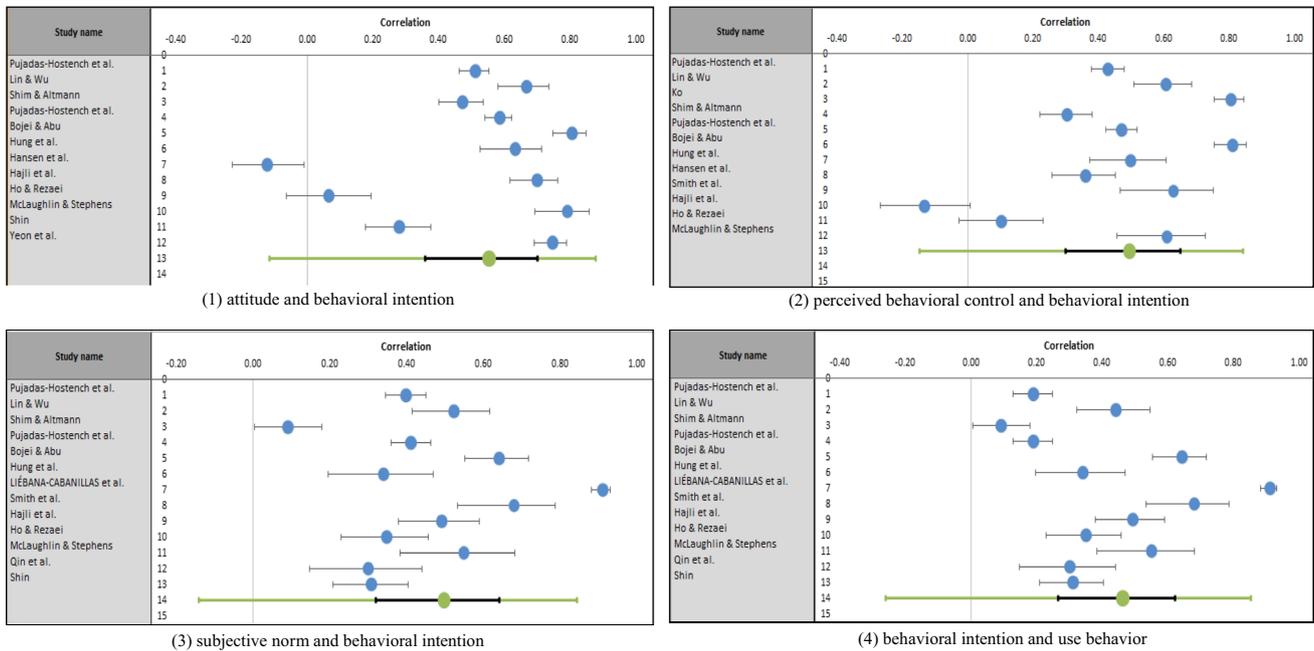
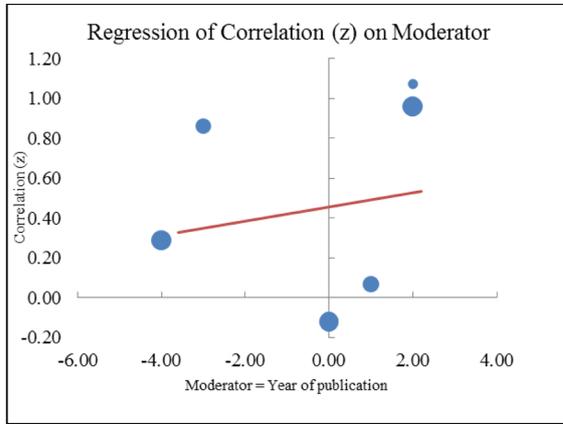
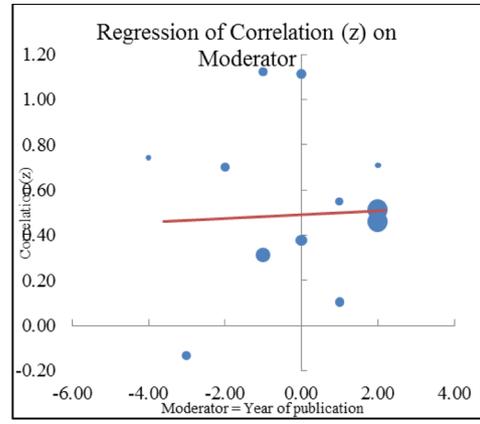


Fig. 7 Forest plots

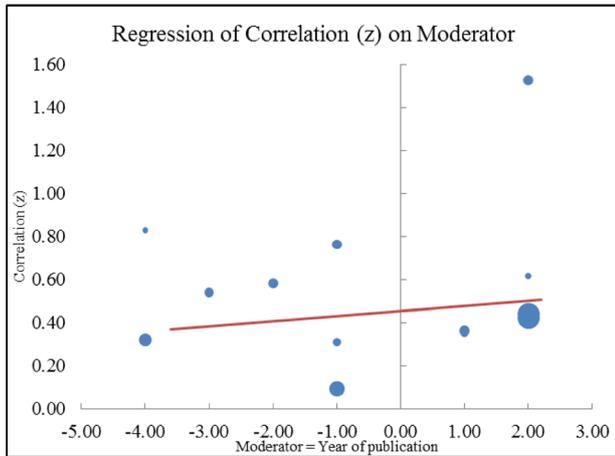
Appendix 5



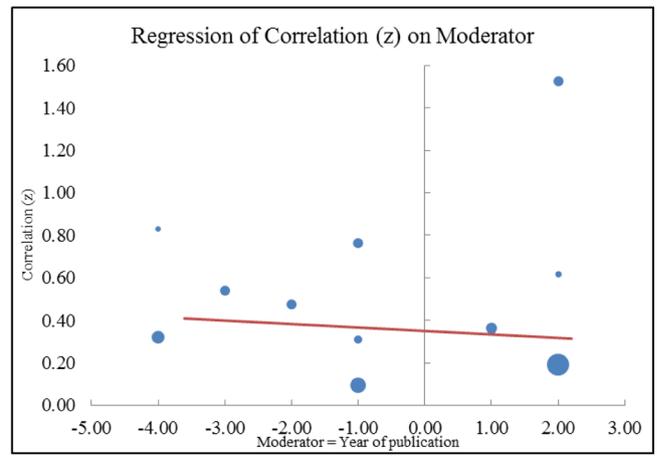
(1) attitude and behavioral intention



(2) perceived behavioral control and behavioral intention



(3) subjective norm and behavioral intention



(4) behavioral intention and use behavior

Fig. 8 Moderation effects

Appendix 6

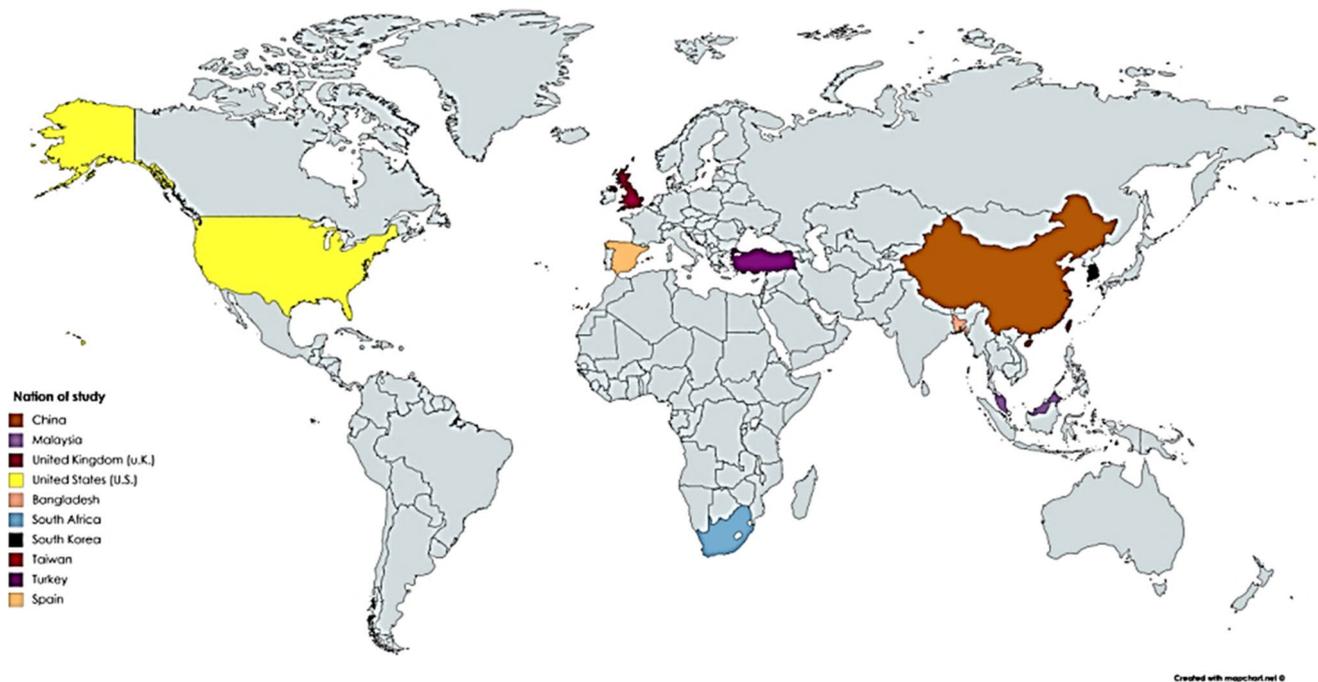


Fig. 9 Distribution of studies across continents

Declarations

Conflict of Interest The authors have no competing interests to declare that are relevant to the content of this article.

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References

- Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of Applied Psychology, 90*(1), 94–107. <https://doi.org/10.1037/0021-9010.90.1.94>
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 665–683. <https://doi.org/10.1111/j.1559-1816.2002.tb00236.x>
- Akman, I. (2014). Exploring Adoption of Social Media Commerce Using Extended Theory of Planned Behaviour. In *International Conference on Economic, Education and Humanities (ICEEH14)* (pp. 10–11). Bali, Indonesia. <https://doi.org/10.15242/icehm.ed1214034>
- Akman, I. (2015). Exploring adoption of social media commerce using extended theory of planned behaviour. In *International conference on economic, education and humanities (ICEEH14)* (pp. 10–11). Bali
- Al-Debei, M. M., Al-Lozi, E., & Papazafeiropoulou, A. (2013). Why people keep coming back to Facebook: Explaining and predicting continuance participation from an extended theory of planned behaviour perspective. *Decision Support Systems, 55*(1), 43–54. <https://doi.org/10.1016/j.dss.2012.12.032>
- Algharabat, R. S., & Rana, N. P. (2021). Social commerce in emerging markets and its impact on online community engagement. *Information Systems Frontiers, 23*(6), 1499–1520. <https://doi.org/10.1007/s10796-020-10041-4>
- Al-Omoush, K. S., de Lucas Ancillo, A., & Gavrila, S. G. (2022). The role of cultural values in social commerce adoption in the Arab world: An empirical study. *Technological Forecasting and Social Change, 176*, 121440. <https://doi.org/10.1016/j.techfore.2021.121440>
- Alsaour, A. (2020). *Social commerce motivations, trust and intentions: An investigation from generational perspectives / Sosyal ticarette motivasyon, güven ve niyetler: Kuşak perspektifinden*

- bir inceleme. Kadir Has University. Retrieved from <http://academicrepository.khas.edu.tr/handle/20.500.12469/4149>.
- Ambalov, I. A. (2018). A meta-analysis of IT continuance: An evaluation of the expectation-confirmation model. *Telematics and Informatics*, 35(6), 1561–1571. <https://doi.org/10.1016/j.tele.2018.03.016>
- Bag, S., Gupta, S., Kumar, A., & Sivarajah, U. (2021). An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance. *Industrial Marketing Management*, 92, 178–189. <https://doi.org/10.1016/j.indmarman.2020.12.001>
- Baker, R. K., & White, K. M. (2010). Predicting adolescents' use of social networking sites from an extended theory of planned behaviour perspective. *Computers in Human Behavior*, 26(6), 1591–1597. <https://doi.org/10.1016/j.chb.2010.06.006>
- Balakrishnan, J., & Dwivedi, Y. K. (2021). Conversational commerce: entering the next stage of AI-powered digital assistants. *Annals of Operations Research*, 1–35. <https://doi.org/10.1007/s10479-021-04049-5>
- Baronas, A. M. K., & Louis, M. R. (1988). Restoring a sense of control during implementation: How user involvement leads to system acceptance. *MIS Quarterly*, 12(1), 111–123. <https://doi.org/10.2307/248811>
- Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. *Industrial Management and Data Systems*, 119(7), 1411–1430. <https://doi.org/10.1108/IMDS-08-2018-0368>
- Bergh, D. D., Aguinis, H., Heavey, C., Ketchen, D. J., Boyd, B. K., Su, P., et al. (2016). Using meta-analytic structural equation modeling to advance strategic management research: Guidelines and an empirical illustration via the strategic leadership-performance relationship. *Strategic Management Journal*, 37(3), 477–497. <https://doi.org/10.1002/smj.2338>
- Berki-Kiss, D., & Menrad, K. (2022). The role emotions play in consumer intentions to make pro-social purchases in Germany – An augmented theory of planned behavior model. *Sustainable Production and Consumption*, 29, 79–89. <https://doi.org/10.1016/j.spc.2021.09.026>
- Blut, M., Yee, A., Chong, L., Tsigna, Z., Venkatesh, V., & Thatcher, J. B. (2022). Meta-analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean. *Journal of the Association for Information Systems*, 23(1), 13–95. <https://aisel.aisnet.org/jais/vol23/iss1/10>. Accessed 31 August 2021.
- Blut, M., Yee, A., Chong, L., Tsigna, Z., Venkatesh, V., & Thatcher, J. B. (2021). Meta-Analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT): Challenging its Validity and Charting a Research Agenda in the Red Ocean. *Journal of the Association for Information Systems*, 23(1), 13–95.
- Bock, G. W., Zmud, R. W., Kim, Y. G., & Lee, J. N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *MIS Quarterly*, 29(1), 87–111. <https://doi.org/10.2307/25148669>
- Bojei, J., & Abu, M. L. (2016). Intention to use social media tools among business-to-consumer (B2C) practitioners in Klang Valley, Malaysia: Insight from TPB. *Malaysian Institute of Management*, 51(2), 57–70.
- Bond, C. F., & Richardson, K. (2004). Seeing the Fisher Z-transformation. *Psychometrika*, 69(2), 291–303. <https://doi.org/10.1007/BF02295945>
- Bu, F., Wang, N., Jiang, B., & Jiang, Q. (2021). Motivating information system engineers' acceptance of Privacy by Design in China: An extended UTAUT model. *International Journal of Information Management*, 60, 102358. <https://doi.org/10.1016/j.ijinfomgt.2021.102358>
- Busalim, A. H., Ghabban, F., & Hussin, A. R. C. (2021). Customer engagement behaviour on social commerce platforms: An empirical study. *Technology in Society*, 64, 160–791. <https://doi.org/10.1016/j.techsoc.2020.101437>
- Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing organizational users' intentions and behavior to AI Integrated CRM systems: a Meta-UTAUT approach. *Information Systems Frontiers*, 1–15. <https://doi.org/10.1007/s10796-021-10181-1>
- Chen, H., Li, L., & Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics*, 8(1), 36–68. <https://doi.org/10.1080/23270012.2020.1852895>
- Cheng, Y. M. (2018). What drives cloud ERP continuance? An integrated view. *Journal of Enterprise Information Management*, 31(5), 724–750. <https://doi.org/10.1108/JEIM-02-2018-0043>
- Choi, J., & Geistfeld, L. V. (2004). A cross-cultural investigation of consumer e-shopping adoption. *Journal of Economic Psychology*, 25(6), 821–838. <https://doi.org/10.1016/j.joep.2003.08.006>
- Chu, T. H., & Chen, Y. Y. (2016). With Good We Become Good: Understanding e-learning adoption by theory of planned behavior and group influences. *Computers and Education*, 92–93, 37–52. <https://doi.org/10.1016/j.compedu.2015.09.013>
- Chung, J. E., Stoel, L., Xu, Y., & Ren, J. (2012). Predicting Chinese consumers' purchase intentions for imported soy-based dietary supplements. *British Food Journal*, 114(1), 143–161. <https://doi.org/10.1108/00070701211197419>
- Combs, J. G., Crook, T. R., & Rauch, A. (2019). Meta-analytic research in management: Contemporary Approaches, unresolved controversies, and rising standards. *Journal of Management Studies*, 56(1), 1–18. <https://doi.org/10.1111/JOMS.12427>
- Conner, M., Sheeran, P., Norman, P., & Armitage, C. J. (2000). Temporal stability as a moderator of relationships in the Theory of Planned Behaviour. *British Journal of Social Psychology*, 39(4), 469–493. <https://doi.org/10.1348/014466600164598>
- Cram, W. A., Templier, M., & Paré, G. (2020). (Re)considering the concept of literature review reproducibility. *Journal of the Association for Information Systems*, 21(5), 1103–1114. <https://doi.org/10.17705/1jais.00630>
- Crook, T. R., Ketchen, D. J., Combs, J. G., & Todd, S. Y. (2008). Strategic resources and performance: A meta-analysis. *Strategic Management Journal*, 29(11), 1141–1154. <https://doi.org/10.1002/smj.703>
- Dionysis, S., Chesney, T., & McAuley, D. (2022). Examining the influential factors of consumer purchase intentions for blockchain traceable coffee using the theory of planned behaviour. *British Food Journal*, pre-print (ahead-of-print), 1–19. <https://doi.org/10.1108/BFJ-05-2021-0541>
- Dwivedi, Y. K., Ismagilova, E., Sarker, P., Jeyaraj, A., Jadhav, Y., & Hughes, L. (2021). A meta-analytic structural equation model for understanding social commerce adoption. *Information Systems Frontiers*, 1–17. <https://doi.org/10.1007/s10796-021-10172-2>
- Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., ..., & Wamba, S. F. (2022a). Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 66, 102542
- Dwivedi, Y. K., Hughes, L., Kar, A. K., Baabdullah, A. M., Grover, P., Abbas, R., ..., & Wade, M. (2022b). Climate change and COP26: Are digital technologies and information management part of the problem or the solution? An editorial reflection and call to action. *International Journal of Information Management*, 63, 102456
- Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a revised theoretical

- model. *Information Systems Frontiers*, 21(3), 719–734. <https://doi.org/10.1007/s10796-017-9774-y>
- Dwivedi, Y. K., Rana, N. P., Tamilmani, K., & Raman, R. (2020). A meta-analysis based modified unified theory of acceptance and use of technology (meta-UTAUT): A review of emerging literature. *Current Opinion in Psychology*, 36, 13–18. <https://doi.org/10.1016/j.copsyc.2020.03.008>
- Esmaeili, L., & Hashemi, G. S. A. (2019). A systematic review on social commerce. *Journal of Strategic Marketing*, 27(4), 317–355. <https://doi.org/10.1080/0965254X.2017.1408672>
- Fischer, R., & Karl, J. A. (2022). Predicting behavioral intentions to prevent or mitigate COVID-19: A cross-cultural meta-analysis of attitudes, norms, and perceived behavioral control effects. *Social Psychological and Personality Science*, 13(1), 264–276. <https://doi.org/10.1177/19485506211019844>
- Friedrich, T. (2016). On the factors influencing consumers' adoption of social commerce – a review of the empirical literature. *Pacific Asia Journal of the Association for Information Systems*, 8(4), 1–32. <https://doi.org/10.17705/1pais.08401>
- Ghosh, M. (2019). Exploring The Factors Influencing Millennials Intention-To-Purchase of Facebook Advertising in Bangladesh. In *SSRN Electronic Journal* (pp. 1–18). Gwalior, India: Prestige Institute of Management, Gwalior. <https://doi.org/10.2139/ssrn.3306490>
- Grand View Research. (2022). *Social Commerce Market Report*. San Francisco, USA. <https://www.grandviewresearch.com/industry-analysis/social-commerce-market>
- Guo, C., Kim, H., & Kim, W. (2020). Influence of word of mouse and consumers attitudes on consumers' decision-making in e-commerce. *Journal of Industrial Distribution & Business*, 11(8), 7–19. <https://doi.org/10.13106/jidb.2020.vol11.no8.7>
- Guo, J. L., Wang, T. F., Liao, J. Y., & Huang, C. M. (2016). Efficacy of the theory of planned behavior in predicting breastfeeding: Meta-analysis and structural equation modeling. *Applied Nursing Research*, 29, 37–42. <https://doi.org/10.1016/j.apnr.2015.03.016>
- Gvili, Y., & Levy, S. (2021). Consumer engagement in sharing brand-related information on social commerce: The roles of culture and experience. *Journal of Marketing Communications*, 27(1), 53–68. <https://doi.org/10.1080/13527266.2019.1633552>
- Hagger, M. S., Chatzisarantis, N. L. D., Barkoukis, V., Wang, J. C. K., Hein, V., Pihu, M., et al. (2007). Cross-cultural generalizability of the theory of planned behavior among young people in a physical activity context. *Journal of Sport and Exercise Psychology*, 29(1), 1–20. <https://doi.org/10.1123/jsep.29.1.2>
- Hagger, M. S., Polet, J., & Lintunen, T. (2018). The reasoned action approach applied to health behavior: Role of past behavior and tests of some key moderators using meta-analytic structural equation modeling. *Social Science and Medicine*, 213, 85–94. <https://doi.org/10.1016/j.socscimed.2018.07.038>
- Hahn, I., Scherer, F., Basso, K., & Santos, M. (2016). Consumer trust in and emotional response to advertisements on social media and their influence on brand evaluation. *Brazilian Business Review*, 13(4), 49–71. <https://doi.org/10.15728/bbr.2016.13.4.3>
- Hair, J. F., Jr., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107. <https://doi.org/10.1504/ijmda.2017.10008574>
- Hajli, N., Shanmugam, M., & Yah Jusoh, Y. (2014). Social Commerce: Theory of Planned Behaviour Perspective. In *BAM 2014 Conference Proceedings* (pp. 1–19). U.K.
- Hajli, N., & Lin, X. (2016). Exploring the security of information sharing on social networking sites: The role of perceived control of information. *Journal of Business Ethics*, 133(1), 111–123. <https://doi.org/10.1007/s10551-014-2346-x>
- Hajli, N., Shanmugam, M., Powell, P., & Love, P. E. D. (2015). A study on the continuance participation in on-line communities with social commerce perspective. *Technological Forecasting and Social Change*, 96, 232–241. <https://doi.org/10.1016/j.techfore.2015.03.014>
- Hamari, J., & Keronen, L. (2017). Why do people play games? A meta-analysis. *International Journal of Information Management*, 37(3), 125–141. <https://doi.org/10.1016/j.ijinfomgt.2017.01.006>
- Han, H., Xu, H., & Chen, H. (2018). Social commerce: A systematic review and data synthesis. *Electronic Commerce Research and Applications*, 30, 38–50. <https://doi.org/10.1016/j.elerap.2018.05.005>
- Hansen, J. M., Saridakis, G., & Benson, V. (2018). Risk, trust, and the interaction of perceived ease of use and behavioral control in predicting consumers' use of social media for transactions. *Computers in Human Behavior*, 80, 197–206. <https://doi.org/10.1016/j.chb.2017.11.010>
- Hassan, L. M., & Shiu, E. (2017). The Role of National Cultural Values within the Theory of Planned Behaviour. In *Developments in Marketing Science: Proceedings of the Academy of Marketing Science* (pp. 813–813). Springer, Cham. https://doi.org/10.1007/978-3-319-50008-9_223
- Hedges, L. V., & Ingram, O. (2014). *Statistical Methods for Meta-Analysis* (1st ed.). Academic Press Inc.
- Heirman, W., & Walrave, M. (2012). Predicting adolescent perpetration in cyberbullying: an application of the theory of planned behavior. *Psicothema*, 24(4), 614–20. <http://www.ncbi.nlm.nih.gov/pubmed/23079360>
- Hew, T. S., Leong, L. Y., Ooi, K. B., & Chong, A. Y. L. (2016). Predicting drivers of mobile entertainment adoption: A two-stage sem-artificial-neural-network analysis. *Journal of Computer Information Systems*, 56(4), 352–370. <https://doi.org/10.1080/08874417.2016.1164497>
- Hew, T. S., & Sharifah, S. L. (2017). The drivers for cloud-based virtual learning environment: Examining the moderating effect of school category. *Internet Research*, 27(4), 942–973.
- Ho, R. C., & Rezaei, S. (2018). Social media communication and consumers decisions: Analysis of the antecedents for intended apps purchase. *Journal of Relationship Marketing*, 17(3), 204–228. <https://doi.org/10.1080/15332667.2018.1492322>
- Ho, S. S., Liao, Y., & Rosenthal, S. (2015). Applying the theory of planned behavior and media dependency theory: Predictors of public pro-environmental behavioral intentions in Singapore. *Environmental Communication*, 9(1), 77–99. <https://doi.org/10.1080/17524032.2014.932819>
- Hofstede, G. H. G. J., & Minkov, M. (2010). *Cultures and organizations: software of the mind: International cooperation and its importance for survival*. (Geert Hofstede, Gert Van Hofstede, & Michael Minkov, Eds.) *The McGraw-Hill Companies, Inc.* (3rd editio, vol. 1). McGraw-Hill.
- Hong, J., He, J., & Qiu, X. (2019). Research on Influencing Factors of Users' Adoption Intention of WeChat Marketing. In *Proceedings - International Joint Conference on Information, Media and Engineering, ICIME 2018* (pp. 152–157). IEEE. <https://doi.org/10.1109/ICIME.2018.00039>
- Hong, W., Chan, F. K. Y., Thong, J. Y. L., Chasalow, L. C., & Dhillon, G. (2014). A framework and guidelines for context-specific theorizing in information systems research. *Information Systems Research*, 25(1), 111–136. <https://doi.org/10.1287/isre.2013.0501>
- Hooda, A., Gupta, P., Jeyaraj, A., Giannakis, M., & Dwivedi, Y. K. (2022). The effects of trust on behavioral intention and use behavior within e-government contexts. *International Journal of Information Management*, 67, 102553.
- Hsu, C. L., Yu, C. C., & Wu, C. C. (2014). Exploring the continuance intention of social networking websites: An empirical research. *Information Systems and e-Business Management*, 12(2), 139–163. <https://doi.org/10.1007/s10257-013-0214-3>

- Hung, S. Y., Yu, A. P. I., & Chiu, Y. C. (2018). Investigating the factors influencing small online vendors' intention to continue engaging in social commerce. *Journal of Organizational Computing and Electronic Commerce*, 28(1), 9–30. <https://doi.org/10.1080/10919392.2018.1407077>
- Ismagilova, E., Rana, N. P., Slade, E. L., & Dwivedi, Y. K. (2021). A meta-analysis of the factors affecting eWOM providing behaviour. *European Journal of Marketing*, 55(4), 1067–1102. <https://doi.org/10.1108/EJM-07-2018-0472>
- Ismagilova, E., Slade, E. L., Rana, N. P., & Dwivedi, Y. K. (2020). The effect of electronic word of mouth communications on intention to buy: A meta-analysis. *Information Systems Frontiers*, 22(5), 1203–1226. <https://doi.org/10.1007/s10796-019-09924-y>
- Javadi, M. H. M., Dolatabadi, H. R., Dashti, M., & Sanayei, A. (2019). Application of the stimuli-organism-response framework to factors influencing social commerce intentions among social network users. *International Journal of Business Information Systems*, 30(2), 177–202. <https://doi.org/10.1504/ijbis.2019.10018673>
- Jeyaraj, A. (2022a). Models of information systems habit: An exploratory meta-analysis. *International Journal of Information Management*, 62, 102436. <https://doi.org/10.1016/j.ijinfomgt.2021.102436>
- Jeyaraj, A. (2022b). A meta-regression of task-technology fit in information systems research. *International Journal of Information Management*, 65, 102493. <https://doi.org/10.1016/j.ijinfomgt.2022.102493>
- Jeyaraj, A., & Dwivedi, Y. K. (2020). Meta-analysis in information systems research: Review and recommendations. *International Journal of Information Management*, 55, 102226. <https://doi.org/10.1016/j.ijinfomgt.2020.102226>
- Jokonya, O. (2016). Validating technology acceptance model (TAM) during IT adoption in organizations. In *Proceedings - IEEE 7th International Conference on Cloud Computing Technology and Science, CloudCom 2015* (pp. 509–516). IEEE. <https://doi.org/10.1109/CloudCom.2015.56>
- Jokonya, O. (2017). Critical Literature Review of Theory of Planned Behavior in the Information Systems Research. In *2nd International Conference on Advances in Management Engineering and Information Technology (AMEIT 2017)* (pp. 177–181). DEStech Publications, Inc. <https://doi.org/10.12783/dtscse/ameit2017/12297>
- Kates, A. W., Wu, H., & Coryn, C. L. S. (2018). The effects of mobile phone use on academic performance: A meta-analysis. *Computers and Education*, 127, 107–112. <https://doi.org/10.1016/j.compedu.2018.08.012>
- Kim, E., Lee, J. A., Sung, Y., & Choi, S. M. (2016). Predicting self-posting behavior on social networking sites: An extension of theory of planned behavior. *Computers in Human Behavior*, 62, 116–123. <https://doi.org/10.1016/j.chb.2016.03.078>
- Kim, K., & Moon, N. (2019). Activity index model for self-regulated learning with learning analysis in a TEL environment. *Journal of Supercomputing*, 75(4), 1971–1989. <https://doi.org/10.1007/s11227-018-2446-y>
- Kim, L. E., Jörg, V., & Klassen, R. M. (2019). A meta-analysis of the effects of teacher personality on teacher effectiveness and burnout. *Educational Psychology Review*, 31(1), 163–195. <https://doi.org/10.1007/s10648-018-9458-2>
- Ko, H. C. (2017). Exploring the factors that influence consumers' social commerce intentions on social networking sites. In *ACM International Conference Proceeding Series* (vol. 15, pp. 1–5). Phuket, Thailand. <https://doi.org/10.1145/3089871.3101109>
- Krasnova, H., Spiekermann, S., Koroleva, K., & Hildebrand, T. (2010). Online social networks: Why we disclose. *Journal of Information Technology*, 25(2), 109–125. <https://doi.org/10.1057/jit.2010.6>
- Leng, G. S., Lada, S., Muhammad, M. Z., Ibrahim, A. A. H. A., & Amboala, T. (2011). An exploration of social networking sites (SNS) adoption in Malaysia using technology acceptance model (TAM), theory of planned behavior (TPB) and intrinsic motivation. *Journal of Internet Banking and Commerce*, 16(2), 1–27.
- Leong, L. Y., Hew, T. S., Ooi, K. B., Chong, A. Y. L., & Lee, V. H. (2021b). Understanding trust in ms-commerce: The roles of reported experience, linguistic style, profile photo, emotional, and cognitive trust. *Information and Management*, 58(2), 1–20. <https://doi.org/10.1016/j.im.2020.103416>
- Leong, L. Y., Hew, T. S., Ooi, K. B., & Dwivedi, Y. K. (2020a). Predicting trust in online advertising with an SEM-artificial neural network approach. *Expert Systems with Applications*, 162(30 December 2020), 113849.
- Leong, L. Y., Hew, T. S., Ooi, K. B., & June, W. (2020b). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management*, 51, 1–24.
- Leong, L. Y., Hew, T. S., Ooi, K. B., Lee, V. H., & Hew, J. J. (2019a). A hybrid SEM-neural network analysis of social media addiction. *Expert Systems with Applications*, 133, 296–316. <https://doi.org/10.1016/j.eswa.2019.05.024>
- Leong, L. Y., Hew, T. S., Ooi, K. B., & Lin, B. (2021a). A meta-analysis of consumer innovation resistance: Is there a cultural invariance? *Industrial Management and Data Systems*, 121(8), 1784–1823. <https://doi.org/10.1108/IMDS-12-2020-0741>
- Leong, L. Y., Hew, T. S., Ooi, K. B., & Tan, G. W. H. (2019b). Predicting actual spending in online group buying – An artificial neural network approach. *Electronic Commerce Research and Applications*, 38, 10898. <https://doi.org/10.1016/j.elerap.2019.100898>
- Liang, T. P., Cheng, J. C., Saini, V., & Hsu, J. S. C. (2021). Is being helpful good enough for online reviews? Exploring the role of information credibility and data source through meta-analysis. *Journal of Electronic Commerce Research*, 22(4), 336–362.
- Liang, T.-P., Ho, Y.-T., Li, Y.-W., & Turban, E. (2011). What drives social commerce: The role of social support and relationship quality. *International Journal of Electronic Commerce*, 16(2), 69–90. <https://doi.org/10.2753/JEC1086-4415160204>
- Liao, S. H., Widowati, R., & Hsieh, Y. C. (2021). Investigating online social media users' behaviors for social commerce recommendations. *Technology in Society*, 66, 101655. <https://doi.org/10.1016/j.techsoc.2021.101655>
- Liébana-Cabanillas, F., Villarejo Ramos, Á. F., Sánchez Franco, M. J. (2014). Mobile social commerce acceptance model: factors and influences on intention to use s-commerce. In *XXVI Congreso Nacional de Marketing* (pp. 1–15). Elche, Alicante, España.
- Liébana-Cabanillas, F., Corral-Hermoso, J. A., Villarejo-Ramos, Á. F., & Higuera-Castillo, E. (2018). New social consumer? Determining factors of Facebook commerce. *Journal of Decision Systems*, 27(4), 213–237. <https://doi.org/10.1080/12460125.2019.1592990>
- Lim, W. M., Kumar, S., Verma, S., & Chaturvedi, R. (2022). Alexa, what do we know about conversational commerce? Insights from a systematic literature review. *Psychology & Marketing*, 39(6), 1129–1155.
- Lin, X., Li, Y., Califf, C. B., & Featherman, M. (2013). Can social role theory explain gender differences in Facebook usage? In *Proceedings of the Annual Hawaii International Conference on System Sciences* (pp. 690–699). IEEE. <https://doi.org/10.1109/HICSS.2013.125>
- Lin, C. S., & Wu, S. (2015). Exploring antecedents of online group-buying: Social commerce perspective. *Human Systems Management*, 34(2), 133–147. <https://doi.org/10.3233/HSM-150837>
- Liobikiene, G., Mandravickaite, J., & Bernatoniene, J. (2016). Theory of planned behavior approach to understand the green purchasing behavior in the EU: A cross-cultural study. *Ecological Economics*, 125, 38–46. <https://doi.org/10.1016/j.ecolecon.2016.02.008>

- Liu, D., Wright, K. B., & Hu, B. (2018). A meta-analysis of social network site use and social support. *Computers and Education*, 127, 201–213. <https://doi.org/10.1016/j.compedu.2018.08.024>
- Ma, T. (Jennifer), & Atkin, D. (2017). User generated content and credibility evaluation of online health information: A meta analytic study. *Telematics and Informatics*, 34(5), 472–486. <https://doi.org/10.1016/j.tele.2016.09.009>
- Markus, H. R., & Kitayama, S. (1991). Culture and the self: Implications for cognition, emotion, and motivation. *Psychological Review*, 98(2), 224–253. <https://doi.org/10.1037/0033-295X.98.2.224>
- McEachan, R. R. C., Conner, M., Taylor, N. J., & Lawton, R. J. (2011). Prospective prediction of health-related behaviours with the theory of planned behaviour: A meta-analysis. *Health Psychology Review*, 5(2), 97–144. <https://doi.org/10.1080/17437199.2010.521684>
- McLaughlin, C., & Stephens, S. (2019). The theory of planned behaviour: the social media intentions of SMEs. In *Irish Academy of Management* (pp. 1–30).
- Meilatinova, N. (2021). Social commerce: Factors affecting customer repurchase and word-of-mouth intentions. *International Journal of Information Management*, 57, 102300. <https://doi.org/10.1016/j.ijinfomgt.2020.102300>
- Mikalef, P., Sharma, K., Pappas, I. O., & Giannakos, M. (2021). Seeking information on social commerce: An examination of the impact of user- and marketer-generated content through an eye-tracking study. *Information Systems Frontiers*, 23(5), 1273–1286. <https://doi.org/10.1007/s10796-020-10034-3>
- Montazemi, A. R., Pittaway, J. J., QahriSaremi, H., & Wei, Y. (2012). Factors of stickiness in transfers of know-how between MNC units. *Journal of Strategic Information Systems*, 21(1), 31–57. <https://doi.org/10.1016/j.jsis.2012.01.001>
- Montazemi, A. R., & Qahri-Saremi, H. (2015). Factors affecting adoption of online banking: A meta-analytic structural equation modeling study. *Information and Management*, 52(2), 210–226. <https://doi.org/10.1016/j.im.2014.11.002>
- Morren, M., & Grinstein, A. (2021). The cross-cultural challenges of integrating personal norms into the Theory of Planned Behavior: A meta-analytic structural equation modeling (MASEM) approach. *Journal of Environmental Psychology*, 75, 101593. <https://doi.org/10.1016/j.jenvp.2021.101593>
- Ng, C. S. P. (2013). Intention to purchase on social commerce websites across cultures: A cross-regional study. *Information and Management*, 50(8), 609–620. <https://doi.org/10.1016/j.im.2013.08.002>
- Nguyen, T. M., Nham, P. T., & Hoang, V. N. (2019). The theory of planned behavior and knowledge sharing: A systematic review and meta-analytic structural equation modelling. *VINE Journal of Information and Knowledge Management Systems*, 49(1), 76–94. <https://doi.org/10.1108/VJIKMS-10-2018-0086>
- Pal, A., Herath, T., De', R., & Rao, H. R. (2021). Is the convenience worth the risk? An investigation of mobile payment usage. *Information Systems Frontiers*, 23(4), 941–961. <https://doi.org/10.1007/s10796-020-10070-z>
- Paré, G., Trudel, M. C., Jaana, M., & Kitsiou, S. (2015). Synthesizing information systems knowledge: A typology of literature reviews. *Information and Management*, 52(2), 183–199. <https://doi.org/10.1016/j.im.2014.08.008>
- Patil, P. P., Rana, N. P., & Dwivedi, Y. K. (2018). Digital payments adoption research: A review of factors influencing consumer's attitude, intention and usage. In S. A. Al-Sharhan, A. C. Simintiras, Y. K. Dwivedi, M. Janssen, M. Mäntymäki, Luay Tahat, et al. (Eds.), *Conference on e-Business, e-Services and e-Society* (vol. 11195, pp. 45–52). Springer, Cham. https://doi.org/10.1007/978-3-030-02131-3_6
- Pavlou, P. A. (2002). What Drives Electronic Commerce? A Theory of Planned Behavior Perspective. In *Academy of Management Proceedings* (vol. 2002, pp. 1–6). Academy of Management. <https://doi.org/10.5465/apb.2002.7517579>
- Pookulangara, S., & Natesan, P. (2010). Examining Consumers' channel-migration intention utilizing theory of planned behavior: a multigroup analysis. *International Journal of Electronic Commerce Studies*, 1(2), 97–116. <http://www.academic-journals.org/ojs2/index.php/ijecs/article/viewFile/919/58>.
- Pujadas-Hostench, J., Palau-Saumell, R., Forgas-Coll, S., & Matute, J. (2019a). Integrating theories to predict clothing purchase on SNS. *Industrial Management and Data Systems*, 119(5), 1015–1030. <https://doi.org/10.1108/IMDS-10-2018-0430>
- Pujadas-Hostench, J., Palau-Saumell, R., Forgas-Coll, S., & Sánchez-García, J. (2019b). Clothing brand purchase intention through SNS. *Online Information Review*, 43(5), 867–892. <https://doi.org/10.1108/OIR-02-2017-0042>
- Qin, L., Kim, Y., & Tan, X. (2018). Understanding the intention of using mobile social networking apps across cultures. *International Journal of Human-Computer Interaction*, 34(12), 1183–1193. <https://doi.org/10.1080/10447318.2018.1428262>
- Quoc, M. (2016). (11). Examples of Conversational Commerce and Chatbots. *Chatbots Magazine by Octane AI*, dated May, 31, 1–24.
- Rabassa, V., Sabri, O., & Spaletta, C. (2022). Conversational commerce: Do biased choices offered by voice assistants' technology constrain its appropriation? *Technological Forecasting and Social Change*, 174, 121292.
- Rana, N. P., Dwivedi, Y. K., & Williams, M. D. (2015). A meta-analysis of existing research on citizen adoption of e-government. *Information Systems Frontiers*, 17(3), 547–563. <https://doi.org/10.1007/s10796-013-9431-z>
- Ratnawati, T., Riyadi, S., & Panjaitan, H. (2017). Subjective norm, moral obligation, and perceived behavioral control, as antecedents variable is service quality, attitude and intention to compliance with taxpayers: (Study on Motor Vehicle Tax in Riau Islands Province). *Journal of Research in Business and Management*, 5(4), 32–40.
- Rhodes, R. E., Courneya, K. S., & Hayduk, L. A. (2002). Does personality moderate the theory of planned behavior in the exercise domain? *Journal of Sport and Exercise Psychology*, 24(2), 120–132. <https://doi.org/10.1123/jsep.24.2.120>
- Rise, J., Sheeran, P., & Hukkelberg, S. (2010). The role of self-identity in the theory of planned behavior: A meta-analysis. *Journal of Applied Social Psychology*, 40(5), 1085–1105. <https://doi.org/10.1111/j.1559-1816.2010.00611.x>
- Rivis, A., & Sheeran, P. (2003). Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis. *Current Psychology*, 22(3), 218–233. <https://doi.org/10.1007/s12144-003-1018-2>
- Rivis, A., Sheeran, P., & Armitage, C. J. (2009). Expanding the affective and normative components of the theory of planned behavior: A meta-analysis of anticipated affect and moral norms. *Journal of Applied Social Psychology*, 39(12), 2985–3019. <https://doi.org/10.1111/j.1559-1816.2009.00558.x>
- Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological Bulletin*, 86(3), 638–641. <https://doi.org/10.1037/0033-2909.86.3.638>
- Ruiz-Mafe, C., Martí-Parreño, J., & Sanz-Blas, S. (2014). Key drivers of consumer loyalty to Facebook fan pages. *Online Information Review*, 38(3), 362–380. <https://doi.org/10.1108/OIR-05-2013-0101>
- Samaha, S. A., Beck, J. T., & Palmatier, R. W. (2014). The role of culture in international relationship marketing. *Journal of Marketing*, 78(5), 78–98. <https://doi.org/10.1509/jm.13.0185>
- Sanne, P. N. C., & Wiese, M. (2018). The theory of planned behaviour and user engagement applied to Facebook advertising. *SA*

- Journal of Information Management*, 20(1), 2–10. <https://doi.org/10.4102/sajim.v20i1.915>
- Sarker, P., Hughe, L., Dwivedi, Y. K., & Rana, N. P. (2020). Social Commerce Adoption Predictors: A Review and Weight Analysis. In *Conference on e-Business, e-Services and e-Society* (vol. 12066, pp. 176–191). Springer, Cham. https://doi.org/10.1007/978-3-030-44999-5_15
- Schepers, J. J. L., & van der Borgh, M. (2020). A meta-analysis of frontline employees' role behavior and the moderating effects of national culture. *Journal of Service Research*, 23(3), 255–280. <https://doi.org/10.1177/1094670520918669>
- Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information and Management*, 44(1), 90–103. <https://doi.org/10.1016/j.im.2006.10.007>
- Sharma, Shwadhin, & Robert, E. C. (2014). Intention to engage in social commerce: Uses and gratifications approach. In *20th Americas Conference on Information Systems, AMCIS 2014* (pp. 1–12). Savannah, Africa.
- Sharma, S., Singh, G., & Sharma, R. (2021). For it is in giving that we receive: Investigating gamers' gifting behaviour in online games. *International Journal of Information Management*, 60, 102363. <https://doi.org/10.1016/j.ijinfomgt.2021.102363>
- Sheeran, P., & Abraham, C. (2003). Mediator of moderators: Temporal stability of intention and the intention-behavior relation. *Personality and Social Psychology Bulletin*, 29(2), 205–215. <https://doi.org/10.1177/0146167202239046>
- Shim, D., & Altmann, J. (2016). How Marginally Does Impulse Buying Intention Change in Social Commerce? Nonparametric Regression Approach Abstract Background and Relevant Research. *Research Article Global Media Journal*, 14(27), 1–13. <http://www.globalmediajournal.com>.
- Shin, D. H. (2013). User experience in social commerce: In friends we trust. *Behaviour and Information Technology*, 32(1), 52–67. <https://doi.org/10.1080/0144929X.2012.692167>
- Shin, D. H., & Kim, W. Y. (2008). Applying the technology acceptance model and flow theory to Cyworld user behavior: Implication of the Web2.0 user acceptance. *Cyberpsychology and Behavior*, 11(3), 378–382. <https://doi.org/10.1089/cpb.2007.0117>
- Singh, S. (2020). An integrated model combining the ECM and the UTAUT to explain users' post-adoption behaviour towards mobile payment systems. *Australasian Journal of Information Systems*, 24, 1–27. <https://doi.org/10.3127/ajis.v24i0.2695>
- Skinner, E. A., Chapman, M., & Baltes, P. B. (1988). Control, means-ends, and agency beliefs: A new conceptualization and its measurement during childhood. *Journal of Personality and Social Psychology*, 54(1), 117–133. <https://doi.org/10.1037/0022-3514.54.1.117>
- Smith, S. M., Zhao, J., & Alexander, M. (2013). Social commerce from a theory of planned behavior paradigm: An analysis of purchase intention. *International Journal of E-Adoption*, 5(3), 76–88. <https://doi.org/10.4018/ijea.2013070104>
- Smith, S. M., Zhao, J., & Alexander, M. (2014). Social Commerce from a Theory of Planned Behavior Paradigm: An Analysis of Purchase Intention. *International Journal of E-Adoption*, 5(3), 76–88. <https://doi.org/10.4018/ijea.2013070104>
- Suh, M., & Hsieh, G. (2016). Designing for future behaviors: Understanding the effect of temporal distance on planned behaviors. In *Conference on Human Factors in Computing Systems - Proceedings* (pp. 1084–1096). Association for Computing Machinery, New York, USA. <https://doi.org/10.1145/2858036.2858591>
- Suurmond, R., van Rhee, H., & Hak, T. (2017). Introduction, comparison, and validation of meta-essentials: A free and simple tool for meta-analysis. *Research Synthesis Methods*, 8(4), 537–553. <https://doi.org/10.1002/jrsm.1260>
- Tajvidi, M., Wang, Y., Hajli, N., & Love, P. E. D. (2021). Brand value Co-creation in social commerce: The role of interactivity, social support, and relationship quality. *Computers in Human Behavior*, 115, 105238. <https://doi.org/10.1016/j.chb.2017.11.006>
- Tamilmani, K., Rana, N. P., Nunkoo, R., Raghavan, V., & Dwivedi, Y. K. (2020). Indian Travellers' Adoption of Airbnb Platform. *Information Systems Frontiers*, 1–20. <https://doi.org/10.1007/s10796-020-10060-1>
- Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2021a). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. *Information Systems Frontiers*, 23(4), 987–1005. <https://doi.org/10.1007/s10796-020-10007-6>
- Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021b). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management*, 57, 102269. <https://doi.org/10.1016/j.ijinfomgt.2020.102269>
- Tariq, J., Sajjad, A., Usman, A., & Amjad, A. (2017). The role of intentions in facebook usage among educated youth in Pakistan: An extension of the theory of planned behavior. *Computers in Human Behavior*, 74, 188–195. <https://doi.org/10.1016/j.chb.2017.04.045>
- Technavio. (2021). Social Commerce Market by Device and Geography - Forecast and Analysis 2020–2024. *Technavio Research*. <https://www.technavio.com/report/social-commerce-market-industry-analysis>. Accessed 13 January 2021
- Templier, M., & Paré, G. (2015). A framework for guiding and evaluating literature reviews. *Communications of the Association for Information Systems*, 37(1), 112–137. <https://doi.org/10.17705/1cais.03706>
- Templier, M., & Paré, G. (2018). Transparency in literature reviews: An assessment of reporting practices across review types and genres in top IS journals. *European Journal of Information Systems*, 27(5), 503–550. <https://doi.org/10.1080/0960085X.2017.1398880>
- Tewari, A., Mathur, S., Srivastava, S., & Gangwar, D. (2022). Examining the role of receptivity to green communication, altruism and openness to change on young consumers' intention to purchase green apparel: A multi-analytical approach. *Journal of Retailing and Consumer Services*, 66, 102938. <https://doi.org/10.1016/j.jretconser.2022.102938>
- Tugba Sabanoglu. (2020). Social commerce sales in the United States from 2019 to 2024. *Statista - The Statistics Portal*. <https://www.statista.com/statistics/277045/us-social-commerce-revenue-forecast/>. Accessed 12 January 2021
- Van Hooft, E. A. J., Born, M. P., Taris, T. W., & Van Der Flier, H. (2006). The cross-cultural generalizability of the theory of planned behavior: A study on job seeking in the Netherlands. *Journal of Cross-Cultural Psychology*, 37(2), 127–135. <https://doi.org/10.1177/0022022105284491>
- Venkatesh, V., & Davis, F. D. (2000). Theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 17(5), 328–376. <https://doi.org/10.17705/1jais.00428>
- Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior*, 120, 106763. <https://doi.org/10.1016/j.chb.2021.106763>
- Viswesvaran, C., & Ones, D. S. (1995). Theory testing: Combining psychometric meta-analysis and structural equations modeling.

- Personnel Psychology*, 48(4), 865–885. <https://doi.org/10.1111/j.1744-6570.1995.tb01784.x>
- Wang, Q., Chau, M., Peng, C. H., & Ngai, E. W. T. (2021). Using the anchoring effect and the cultural dimensions theory to study customers' online rating behaviors. *Information Systems Frontiers*, 1–13. <https://doi.org/10.1007/s10796-021-10148-2>
- Wang, X., & Goh, D. H. L. (2017). Video game acceptance: A meta-analysis of the extended technology acceptance model. *Cyberpsychology, Behavior, and Social Networking*, 20(11), 662–671. <https://doi.org/10.1089/cyber.2017.0086>
- Wang, Y., Wang, J., Yao, T., Li, M., & Wang, X. (2020). How does social support promote consumers' engagement in the social commerce community? The mediating effect of consumer involvement. *Information Processing and Management*, 57(5), 102272. <https://doi.org/10.1016/j.ipm.2020.102272>
- Wong, C. H., Tan, G. W. H., Loke, S. P., & Ooi, K. B. (2014). Mobile TV: A new form of entertainment? *Industrial Management and Data Systems*, 114(7), 1050–1067. <https://doi.org/10.1108/IMDS-05-2014-0146/FULL/XML>
- Wong, C. H., Tan, G. W. H., Loke, S. P., & Ooi, K. B. (2015). Adoption of mobile social networking sites for learning? *Online Information Review*, 39(6), 762–778. <https://doi.org/10.1108/OIR-05-2015-0152>
- Wong, L. H. M., Hurbean, L., Davison, R. M., Ou, C. X., & Muntean, M. (2022). Working around inadequate information systems in the workplace: An empirical study in Romania. *International Journal of Information Management*, 64, 102471. <https://doi.org/10.1016/j.ijinfomgt.2022.102471>
- Wu, J., & Du, H. (2012). Toward a better understanding of behavioral intention and system usage constructs. *European Journal of Information Systems*, 21(6), 680–698. <https://doi.org/10.1057/ejis.2012.15>
- Yeo, V. C. S., Goh, S. K., & Rezaei, S. (2017). Consumer experiences, attitude and behavioral intention toward online food delivery (OFD) services. *Journal of Retailing and Consumer Services*, 35, 150–162. <https://doi.org/10.1016/j.jretconser.2016.12.013>
- Yeon, J., Park, I., & Lee, D. (2019). What creates trust and who gets loyalty in social commerce? *Journal of Retailing and Consumer Services*, 50, 138–144. <https://doi.org/10.1016/j.jretconser.2019.05.009>
- Zaremohzzabieh, Z., Ahrari, S., Krauss, S. E., Samah, A. B. A., Meng, L. K., & Ariffin, Z. (2019). Predicting social entrepreneurial intention: A meta-analytic path analysis based on the theory of planned behavior. *Journal of Business Research*, 96, 264–276. <https://doi.org/10.1016/j.jbusres.2018.11.030>
- Zhang, K. Z. K., Gong, X., Zhao, S. J., & Lee, M. K. O. (2015). Cognitive trust, emotional trust and the value-based acceptance model in mobile payment adoption. In *Proceedings of the International Conference on Electronic Business (ICEB)* (Vol. 2015-January, pp. 166–174). Sha Tin, Hong Kong. <https://www.scopus.com/inward/record.uri?eid=2-s2.0-84959227682&partnerID=40&md5=da9ad9988bc7ab5d0e346e8acf61ca80>
- Zhang, L., Zhu, J., & Liu, Q. (2012). A meta-analysis of mobile commerce adoption and the moderating effect of culture. *Computers in Human Behavior*, 28(5), 1902–1911. <https://doi.org/10.1016/j.chb.2012.05.008>
- Zhang, Z., & Wang, H. (2019). How online social ties and product-related factors influence purchasing intention in mobile social commerce context. *International Journal of Mobile Communications*, 17(2), 191. <https://doi.org/10.1504/ijmc.2019.098063>
- Zhao, Y., Li, Y., Wang, N., Zhou, R., & Luo, X. (Robert). (2021). A meta-analysis of online impulsive buying and the moderating effect of economic development level. *Information Systems Frontiers*, 1–22. <https://doi.org/10.1007/s10796-021-10170-4>
- Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management*, 43, 342–350. <https://doi.org/10.1016/j.ijinfomgt.2017.08.006>

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