MOBILE COMMERCE, CROWD COMMERCE, AND STAGE MODELS –REVIEWING AND EXPANDING ON TP LIANG'S RESEARCH

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ABSTRACT

In this paper, we review a few key themes of Ting-Peng (TP) Liang's research. We first discuss some of his major contributions to information systems (IS) in the areas of *electronic commerce*, *mobile commerce*, and *crowd commerce*. Future research directions for these three themes are also discussed in the paper. TP Liang is also an early proponent of stage models although this stream of research has yet to receive the importance it deserves in the IS community. Previous seminal theoretical accounts in IS have generally separated variance and process models, the latter is useful in modeling changes in the explanatory or predictive variables. In other sciences such as various branches of psychology, change or development is commonly modeled by stages (i.e., stage models). We proffer TP Liang as an important early proponent of stage models.

Keywords: Stage models; Electronic commerce; Mobile commerce; Crowd commerce

1. Introduction

Ting-Peng (TP) Liang, former president of the Association for Information Systems, was a pioneering figure and thought leader of information systems (IS), especially in the Pacific Asia region. TP Liang is well known for establishing several noteworthy activities in this region, including the Pacific Asia Conference on Information Systems (PACIS) and the Pacific Asia Journal of the Association on Information Systems (PAJAIS). In this paper, we review some of TP Liang's major themes in IS research.

TP Liang is also one of the most prolific and cited authors in the IS field. According to Google Scholar, he has produced over 300 publications, including journal articles, book chapters, conference papers, and working papers. Moreover, his research articles have been cited nearly 30,000 times (as of August 2021). TP Liang's work is exceptionally diverse, including research areas such as electronic commerce (Liang & Huang, 1998; Liang & Doong, 2000; Liang et al., 2006; Liang et al., 2008), decision support systems (Liang, 1985, 1986), strategic IS (Liang, You, & Liu, 2010; Wu, Straub, & Liang, 2015; Grover, Chiang, Liang, & Zhang, 2018), knowledge management (e.g., Chen, Liang, & Lin, 2010), service innovation (e.g., Liang & Lu, 2013), and intelligent systems (e.g., Liang et al., 2021). He also contributed to advancing neuroscience research in the IS field (Liang & Vom Brocke, 2014; Vom Brocke & Liang, 2014).

In the next section, we review three areas to which TP Liang devoted his efforts in the domain of electronic commerce. After that, we focus on highlighting one of his broader contributions that is currently undervalued: his seminal use of stage models. We compare stage models to variance and process models in IS, and highlight that the stage model view as advocated by TP Liang shows great promise for future IS research to model change.

2. Three Main TP Liang's Research Themes

Considering his prolific track record, we limit our tribute to presenting TP Liang's most notable contributions to the domain of electronic commerce. In this field, three research themes deserve our attention: (1) Liang's early writings on *electronic commerce* (Liang & Huang, 1998; Liang & Doong, 2000; Liang & Lai, 2002; Liang et al., 2006; Ho et al., 2007; Liang et al., 2008); (2) his work on *mobile commerce* (Liang & Wei, 2004; Tsang et al., 2004; Liang & Yeh, 2011; Liang, Ling, Yeh, & Lin, 2013; Liang, Li, Yang, & Wang, 2015); and (3) his research on *crowd commerce* (Liang et al., 2011; Liang & Turban, 2011; Chiu et al., 2014; Liang et al. 2019; Liang et al., 2021). The appendix provides more detailed insights from these selected articles.

2.1. Electronic Commerce

The first research theme is Liang's early work on **electronic commerce.** Electronic commerce (or e-commerce) is one of the earliest research topics exploring the transition from traditional commerce (e.g., in physical shops) to cyberspace (e.g., the Internet). Liang and Huang (1998) defined e-commerce as a "business practice associated with the buying and selling of information, products, and services via the Internet" (Liang & Huang, 1998, p. 29). Various e-commerce models exist, including business-to-business (B2B), business-to-consumer (B2C), and consumer-to-consumer (C2C). In this overview, we focus mainly on Liang's work on the B2C model, which he described as "the use by business and consumers of the global Internet for the sale and purchase of goods and services, including business services and support after the sale to consumers" (Ho et al., 2007, p. 238). TP Liang's work on e-commerce covers various contexts, including e-stores (Liang & Doong, 2000; Liang & Huang, 1998; Liang & Lai, 2002), news websites (Liang et al., 2006), and online library platforms (Liang et al., 2008). One of the central questions in this body of work revolves around the determinants of consumer online shopping decisions. For instance, based on transaction cost theory (TCT), Liang and Huang's (1998) work showed that consumer acceptance of products online are affected by transaction cost, which is determined by the uncertainty in electronic shopping and product specificity. Further, they emphasized the role of consumer experience in shaping online shopping decisions (i.e., "the learning effect"). Specifically, Liang and Huang (1998) suggested that whereas inexperienced shoppers were concerned with both uncertainty and product specificity, experienced shoppers are concerned with experiencing uncertainty when doing online shopping. From a store design perspective, Liang and Lai (2002) proposed that online shoppers were more likely to conduct transactions on well-designed websites. Liang and Lai (2002) examined the impact of three categories of factors on perceptions of design quality: *hygiene factors* (e.g., website security), *motivators* (e.g., ease of signing up), and *media richness factors* (e.g., navigational hyperlinks). Their findings indicated that hygiene factors were critical when consumers decided whether to shop electronically, while motivational factors were more important when choosing among different electronic stores. Media richness factors were deemed least important, at least in the context of digital bookstores (Liang & Lai, 2002). Further research can extend this area to investigate C2C commerce. Also, electronic commerce has advanced significantly since the early days of research in this field. Direct to consumer (D2C) e-commerce is one of the latest trends. Others including the use of AI and big data to create personalized shopping experiences and chatbots to support shoppers. Thus, replicating and expanding on some of the previous studies may shed new lights on the determinants of online shopping decisions.

From yet another perspective, Liang's work addresses the role of personalized recommendation systems in the consumer decision-making process (Liang et al., 2006, 2008). Personalized recommendation systems are central to many, if not most, modern e-commerce applications. According to the Personalization Consortium, personalization entails "the use of technology and customer information to tailor electronic commerce interactions between a business and each individual customer" (as cited in Liang et al., 2006, p. 47). Hence, a recommendation system is an information system that uses information about an individual consumer as a basis to provide product or service suggestions that potentially meet that consumer's needs (Liang et al., 2006, 2008). A key objective of personalized recommender systems "is to reduce irrelevant content and provide users with more pertinent information or product" (Liang et al., 2008, p. 401). Broadly speaking, two common methods are used to collect users' preferences: an explicit and an implicit method. In the *explicit method*, users are asked to express their preferences explicitly—for example, via feedback requests and questionnaires. In the *implicit method*, the user's preferences are inferred by capturing the user's browser data, such as visited websites and searched words (Liang et al., 2006). In the context of online news consumption, Liang et al. (2006) examined the role of personalization and recommendation accuracy in explaining user satisfaction. The findings revealed that recommendation systems that made more accurate content recommendations had a significant and positive impact on user satisfaction. Surprisingly, however, the study found that contrary to user involvement theory, users' feedback in personalized services had no significant impact on their levels of satisfaction. Since that seminal work, the technology has evolved significantly and team or group recommendation systems are now available, and future research should take such development into consideration. For example, personalized recommendation systems in the consumer decision-making process can now act as group recommendation systems in order to support the group collectively (e.g., a group of friends shopping online at the same time) rather than providing personalized recommendations to only individuals. Also, future studies can be conducted on different types of recommendation systems (e.g., collaborative recommender system, content-based recommender system, demographic-based recommender system, utility-based recommender system, and so on). Furthermore, the advancement in AI and machine learning provides new capabilities to recommendation systems. These new features and characteristics of recommendation systems may produce different outcomes compared to early versions of recommendation systems.

TP Liang's work on e-commerce addresses macro-level questions as well. One such question is determining the extent to which growth in e-commerce revenues at the country level is driven by internal or external factors (Ho et al., 2007). The theoretical framework adopted in this work is based on growth theory (or theories), which, as Ho et al. (2007) pointed out, is "associated with models, mechanisms, explanations and predictive frameworks that characterize what drives a country's economic growth" (p. 241). Three models of national economic growth (or technical progress) informing Liang's work are worth noting briefly here. The first model is referred to as the *exogenous growth theory* (also known as neoclassical growth theory), which assumes that the long-term growth of a given system (e.g., country or region) can only be explained by uncontrollable and exogenous components of the production function, such as geographical location, natural resources, and technological development in other nations (Ho et al., 2007). By contrast, the second model, often referred to as the *endogenous growth theory*, argues that economic growth happens due to forces from within the economic system and is not the result of external and uncontrollable factors operating from the outside, as assumed by the exogenous growth model. Unlike neoclassical growth theory, the core of endogenous growth theory "is that economic growth involves a two-way interaction between technology and economic life: technological progress transforms the very economic system that creates it" (Ho et al., 2007, p. 242). By combining these two perspectives, Ho et al. (2007) provided a third model, which is a more elaborate explanation for the growth of e-commerce at the national level by accounting for both external forces (e.g., the level of e-commerce development in other influential countries) and internal forces (e.g., Internet penetration level among citizens, their education level, and availability of online payment systems). Much work remains to be done in this area especially in the areas of e-commerce policies (e.g., taxation, regulations) and governance.

2.2. Mobile Commerce

The second research theme is **mobile commerce.** Mobile commerce (or m-commerce) represents a strand of electronic commerce in which transactions are executed via mobile phones (Siau & Shen, 2003). More specifically, m-commerce refers to "utilising mobile hand-held devices and […] wireless communication networks to conduct a commercial transaction and its related interactive business processes that occur before and after actual sales transactions" (Liang et al., 2013, p. 315). These transactions may be for purely electronic business purposes, such as "product ordering, fund transfers, and stock trading" (Liang and Wei, 2004, p. 7), or for entertainment purposes, such as mobile gaming and watching videos (Liang & Yeh, 2011; Liang et al., 2013). In this sense, mobile commerce extends traditional e-commerce applications by benefiting from various capabilities that were not possible before the introduction and widespread adoption of handheld (and smart) phones. Among the most notable characteristics of mobile-based commerce are (1) *ubiquity*, or the ability to reach the user anytime and anywhere; (2) *location awareness*, or the ability to identify and track location; and (3) *authentication*, or the ability to verify the user's identity (Liang & Wei, 2004). Looking at the evolution of m-commerce as a research topic, Liang and Yeh (2011) recognized that while early research efforts on e-commerce mainly focused on the categorization and identification of application opportunities for m-commerce, more recent studies focused more on understanding the impact of contextual factors on the adoption and usage of m-commerce and services (Liang & Yeh, 2011).

In the early days of m-commerce, many mobile applications and services were hit-and-miss attempts, which stressed the need to develop frameworks that capture what might explain m-commerce success. Liang and Wei (2004) proposed a two-dimensional fit-viability framework to evaluate m-commerce initiatives: "*fit* measures the extent to which the capabilities of mobile technology meet the requirement of the task, and *viability* measures the extent to which the environment or organization is ready for the application" (p. 11). As such, application developers should focus their efforts on applications that have (a) a good fit between the task to be executed and the characteristics of mobile technology and (b) strong economic and social viability in the application context and environment. Undoutedly, one of the key indicators of the success of m-commerce services is their adoption and use by their intended users. Therefore, one central objective of TP Liang's work on m-commerce has been to identify the factors that predict (or explain) the sales in mobile applications (Liang et al., 2015) and the continued use intentions of their users (Liang & Yeh, 2011; Liang et al., 2013). Regarding mobile app sales, Liang et al. (2015) examined the impact of sentiment in user reviews, or electronic word-of-mouth (eWOM), on mobile applications' sales on the iOS app store in Taiwan and found that reviews do have a significant influence on app sales rankings. The study further showed that, especially for free apps, users care about the service and product quality expressed in reviews. Regarding users' intentions to continue using m-commerce applications, TP Liang's work indicates that the use-context matters (Liang & Yeh, 2011; Liang et al., 2013). For instance, in the context of mobile gaming, Liang and Yeh (2011) examined the impact of various contextual factors on users' intention to play a game. Contextual factors focused on two dimensions: task and location. The task dimension captured whether a user had a task at hand or was free (i.e., did not have a task at hand). The location dimension captured whether a user was at home or at work/school. The study findings revealed that these contextual factors did have an impact on the formation of users' attitudes and playing intentions. For instance, when users were free (i.e., had no other obligation or task at hand), their intentions to play mobile games were determined primarily by personal attitudes and subjective norms (i.e., perceptions of whether reference groups agreed on playing games). By contrast, when they played the mobile game under the pressure of being busy (i.e., having another obligation or task to complete), the users' intentions to play the game were dominated solely by their personal attitudes toward the mobile game.

In terms of future research opportunities, TP Liang's research has set the stage for several possibilities. For example, Liang and Yeh (2011) suggest that use context matters and one stream of future research is to look at the different use contexts for mobile commerce. Mobile gaming has a huge market and tremendous potential. Mobile games need to overcome several constraints that are less of an issue with computer games. For example, the small screen size, lower connection speed, lesser processing power, and less stable connection are limitations that need to be considered in mobile games development. Also, the notion of flow (Nah et al. 2011) is much harder to achieve with the limitations of mobile games and flow is important in playing a game and to sustain players' interest in a game. The study of factors that impact a mobile game's success will have significant practical value for game developers.

2.3. Crowd Commerce

The third research theme is **crowd commerce.** The name comes from this theme's emphasis on contemporary technologies that enable value-creating mechanisms from the crowd, or traditional consumers and users (Grover et al., 2018). These technologies, typically referred to as Web 2.0 technologies (Blank & Reisdorf, 2013), have allowed new forms of user-generated resources (e.g., blogs, forums, reviews, ratings, and so on) to enter the commerce equation. Not only have these modern technologies enabled new information sources to influence the consumer decision-making process, but they have also facilitated the introduction of novel crowd-based business models, including social commerce (Liang et al., 2011; Liang & Turban, 2011), crowdsourcing (Chiu et al., 2014), crowdfunding (Liang et al., 2019), and the sharing economy (Liang, et al., 2021), to name a few. One of the earliest crowd commerce innovative applications was the result of integrating qualities from both e-commerce and social networking to produce what was called social commerce (Liang et al., 2011). Social commerce, as such, describes "the delivery of e-commerce activities and transactions via the social media environment, mostly in social networks and by using Web 2.0 software" (Liang & Turban, 2011, p. 6). Users of social commerce platforms typically utilize the platform as a medium to interact with their friends and peers to share product information, sell products and services, and/or seek advice from the community regarding their purchasing decisions (Liang et al., 2011). Given the critical role the social community plays in this type of commerce, empirical research has found that social support—understood as an "individual's experiences of being cared for, being responded to, and being helped by people in that individual's social group" (Liang et al., 2011, p. 71)—is a significant contributor to explaining both social commerce use intention and loyalty to the platform. Strong growth is anticipated for the future of social commerce. Future research possibilities could explore the impact of the emerging social norms and practices on spending and purchasing decisions. Emerging practices include influencers and their impact on followers, shoppable instagram feeds on websites, video and live streaming such as TikTok, the use of AI and conversational chatbots in social commerce, to name a few.

A slightly different form of crowd commerce addressed by TP Liang's research is crowdsourcing. Crowdsourcing is "an umbrella term for a set of tools, approaches and concepts that deal with the process of outsourcing work (including seeking ideas) to a large and possibly unknown group of people (the crowd)" (Chiu et al., 2014, p. 40). As a typical two-sided market, crowdsourcing platforms orchestrate the matching of demand and supply between two parties: requesters and solvers. On the one hand, *the requester* (i.e., the seeker or crowdsourcer) is an organization (or a person) that needs a specific task to be performed. On the other hand, *solvers* (i.e., crowdworkers) are individuals who are potentially willing and able to fulfill the task. Crowdsourcing platforms vary profoundly depending on at least two dimensions: crowd contributions and task recurrence (Soliman & Tuunainen, 2015, 2021). Whereas the contribution dimension (e.g., selective or integrative) determines the level of rivalry expected among the platform participants, the recurrence dimension (e.g., recurring or one-off) determines the level of continuity of a given crowdsourcing project. Chiu et al.'s (2014) literature review points to various applications in which crowdsourcing has been popular. Such applications include (1) *collective intelligence*, in which case the crowd is invited to solve problems and provide new insights leading to the identification of novel products, processes, or service innovations; (2) *user-generated content*, where the crowd is invited to create/generate different types of content (e.g., music, photos, blogs, etc.) and share it with others for a fee; and (3) *crowd voting*, where the crowd is invited to give their opinion and ratings on various subjects of interest, such as ideas, products, and/or services. Building on Herbert Simon's decision-process model, which breaks down managerial decision-making before implementation into three stages (intelligence, design, and choice), Chiu et al. (2014) showed how different crowdsourcing applications could provide support to managers at different stages of the decision-making process. For instance, during the *intelligence stage*, crowdsourcing could be used to help managers better understand a given problem and/or search for an optimal solution via search and discovery models. During the *design stage*, crowdsourcing may be used to generate innovative ideas and solutions via collaborative or competitive models. During the *choice stage*, crowdsourcing could help managers choose the right course of action via voting and preference-identification models. In addition to the three crowdsourcing models mentioned earlier, a fourth model (namely, crowdfunding) has received exceptionally special attention, probably due to its capital-attracting nature. Liang et al. (2019) defined crowdfunding as "an open call for funding via donation or in exchange for a reward in order to support specific projects and initiatives typically through the Internet" (Liang et al., 2019, p. 70). One of the pressing needs in this area of research is to understand which factors drive crowdfunding investment intention and behavior. From the point of view of trust theory, Liang et al. (2019) found funders' trust in a given project creator to be a significant determinant of the crowd's intention to invest in that project. Trust itself was determined by (a) *cognition-based factors* (namely, the fundraisers' expertise and the project's information quality), and (b) *affect-based factors* (namely, the value similarity between the funder and fundraiser). Interestingly, the study revealed that the funder's general disposition to trust did not play a role in trust formation. Considering the nascence of this research topic, future research possibilities are vast, including, for example, exploring the different strategies for macrotasks and microtasks, designing crowdsourcing processes to make them more effective, and adoption issues related to crowdsourcing.

The sharing economy is yet another crowd-based commerce model that represents "people coordinating the acquisition and distribution of a resource for a fee or other compensation, such as bartering, trading, and swapping" (Liang et al., 2021, p. 2). The sharing economy is often considered a special case of crowdsourcing, since, at its core, sharing-economy platforms facilitate generating value from people's (i.e., the crowd's) underutilized resources, such as time, money, possessions, and so on. The applications of the sharing-economy model are numerous, and Liang et al. (2021) pointed to several prominent examples: peer-to-peer transportation (e.g., Uber) and peer-to-peer accommodation (e.g., Airbnb), to name a few. Two dimensions are critical in shaping the structure of a sharing-economy platform: (a) rivalry between platform participants and (b) control exerted by the platform owner. Variation in the intensity of these two dimensions points to four prototypical sharing-economy models: Franchiser, Principal, Chaperone, and Gardener (Constantiou et al., 2017). First, *Franchiser* platforms exercise absolute control over the entire transaction and have the power to set and modify the service exchange price as they see fit (e.g., Uber). Second, *Chaperone* platforms, by contrast, act as mere overseers and exert a loose control over the transactions that occur among participants on the platform (e.g., Airbnb). Both Franchisers and Chaperones foster high levels of rivalry among their participants. Third, *Principal* platforms focus heavily on standardizing the service provision by enforcing rules and monitoring performance on the supplier side. In contrast to the Franchiser and Chaperone models, prices on the Principal model are fixed and predefined, which explains the low rivalry among supply-side participants (e.g., TaskRabbit). Fourth, *Gardener* platforms exert the lowest level of control, as well as rivalry, among participants. They see that their main role is to cultivate a community, and they seek voluntary contributions from the participants (e.g., Couchsurfing) (Constantiou et al., 2017). Considering the novelty of the topic, one of the key questions here is what drives users to use sharing-economy platforms. By combining the value-based adoption model (VAM) and transaction cost theory (TCT), Liang et al. (2021) revealed that the intention to use a sharing platform was well predicted by perceived value, which in turn could be increased by reducing transaction costs and increasing the perceived economic benefits (e.g., money and time benefits) and non-economic benefits (e.g., social epistemic benefits) of transactions on the platform. Although the sharing economy has been affected by the pandemic, it is expected to survive and make a strong come back in the post pandemic era or in the new normal.

3. Stage Models in TP Liang's Work

In our view, one of the most vital aspects of TP Liang's work is his recognition of the importance of stage models/theories in his work, as well as the IS domain. As noted by Rivard (2014), "most theoretical models that are developed in the IS domain are either variance or process models" (p. ix). The distinction between variance and process stems from Mohr (1982) as recognized by many IS scholars (Burton-Jones et al., 2015; Lyytinen & Newman, 2008; Newman & Robey, 1992; Sabherwal & Robey, 1993; Tsohou et al., 2019). The variance models might be better called stage-less models/theories (Velicer & Prochaska, 2008) or continuum theories (Weinstein et al., 1998) – the nomenclature used in many other disciplines such as developmental psychology, health psychology, psychiatry, and moral psychology (Karjalainen et al., 2020). The basic assumption and limitation of stage-less models are that their predictive or explanatory variables cannot change over time (Karjalainen et al., 2019). Take the ease of use from the technology acceptance model (TAM) as an example. The TAM views ease of use as a "fundamental determinant" of users' acceptance of IT (Davis, 1989, p. 319). As it turns out, the TAM cannot explain cases in which a predictive or explanatory variable can change over time. Consider, for example, ease of use from TAM and mobile apps. First, a user goes to an app store and searches for various apps. Second, s/he decides to download a particular app. Logically, ease of use is hardly a predictive or explanatory variable in these stages. Price, catchy name, or someone's recommendation could instead be the predictive or explanatory variables. However, when a person uses the app, ease of use could be a predictive or explanatory variable. Later on, the use of the app can be habitual or the user may quit using it—and none of the reasons for these outcomes is necessarily related to ease of use (Soliman & Rinta-Kahila, 2020; Soliman & Tuunainen, 2021).

If stage-less or "variance" models have a hard time explaining user behavior in such cases, can process theories help? In principle, yes. However, major accounts of process theories deem them "eventwise" (Rivard, 2014, p. ix). For example, both Mohr (1982) and Pentland (1999, p. 711, 721) saw stage theories as consisting of events. Mohr (1982) noted how "a processes theory deals with a final cause" and "events." In turn, Pentland (1999) viewed process theory as "an explanation […] that describes the process, or sequence of events, that connects cause and effect" (p. 711). In other words, "an explanation is basically a process theory—a hypothesis about a causal sequence of events" (Pentland, 1999, p. 721). While a review of the fundamentals of process theories cannot be accomplished here, the idea of a process as a series of events also limits what can be counted as a process model. For instance, in the TAM example above, the key issue may not be an event but different stages of IT use. In such situations, stage theories could be useful. Stage theories or models are helpful when explanatory or predictive factors are assumed not to be the same during the life cycle of the phenomenon in question (Tsohou et al., 2019). Put differently, according to stage models, the predictive factors or explanations may change over the life cycle of a phenomenon (Karjalainen et al., 2020). Stages models attempt to capture this change or development by linking it to stages. One fundamental requirement for a stage model is to have at least some stage-specific explanatory or predictive factors or attributes (Weinstein et al. 1998). This is seen as a fundamental criterion. If no stage-specific factor(s) are found, there would be no need for a stage model (Tsohou et al., 2019). By comparison, for stage-less or non-stage models, factors or explanations that either explain or predict the phenomenon of interest are assumed to be invariant/unchanged (Karjalainen et al., 2020; Tsohou et al., 2019).

Arguably, while some stage models exist in IS (Karjalainen et al., 2020; Schwarz et al., 2014; Soliman & Tuunainen, 2021; Tsohou et al., 2019), these models have not received the wide interest they deserve in the field, as statements such as "most theoretical models that are developed in the IS domain are either variance or process models" (Rivard 2014, p. ix) imply.

We would like to nominate TP Liang as a key contributor to stage models in IS. Let us look at some of the stage models that influenced TP Linag's work. For instance, Liang and Lai (2002) adopted the consumer choice model (also known as EKB). The EKB models the consumer decision process into five stages: 1. problem recognition, 2. search for information, 3. evaluation of alternatives, 4. choice, and 5. outcome evaluation. The authors explain, "When a problem is recognized, demand for products that can eliminate the problem occurs. Product information is collected and alternatives are evaluated. Once an alternative is chosen, the consumer executes the transaction, evaluates the outcome, and saves the experience for the future" (p. 433). Interestingly, Liang and Lai (2002) acknowledged the importance of recognizing and identifying stage-specific factors.

In other work, both **Liang (1986)** and **Chiu et al. (2014)** adopted Herbert Simon's decision-making stage theory. Simon's theory models the human decision process as four stages: 1. intelligence: the user searches his/her experience and knowledge base to identify problems and collect relevant information; 2. design: the user invents, analyzes, and evaluates possible courses of action; 3. choice: the user decides on the best course of action; and 4. feedback: after making the decision, the outcome becomes an additional piece of knowledge that will be used in a future intelligence stage, thus affecting future behavior. By modeling the decision making process of managers around sequencal stages, TP Liang's gave us a lens to realize that one would expect that different factors and more or less relevant to different stages (Chiu et al., 2014; Liang, 1986). For instance, in the context of crowdsourcing, TP Liang's work convincingly shows that not all crowdsourcing applications are relevant to all stages of the decision making process. Rather, the crowds can play different roles at different stages. Crowdsourcing solutons that are relevant in the intelligence stage (e.g., search and discovery) may be irrelevant and even counterproductive in a later stage, such as the design or choice stages (Chiu et al., 2014).

As our final example, **Liang and Huang (1998)**, who developed a seven-stage transaction model based on various customer decision models. The stages in their model are: "1. Search: search for relevant product or service information. 2. Comparison: compare prices or other attributes. 3. Examination: examine the products to be purchased. 4. Negotiation: negotiate terms, e.g., price, delivery time, etc. 5. Order and payment: place an order and pay for it. 6. Delivery: delivery of products from the seller to the customer. 7. Post-service: customer service and support" (Liang & Huang, 1998, p. 31). Before introducing this model, Liang and Huang (1998) acknowledged the existence of several other relevant decision models with slightly different focus and emphasis, including the customer decision process, the customer resource lifecycle, as well as the mercantile model. While these models converge in their aim (i.e., to capture the stages that consumers go through in their typical pursuit of a product/service); they mainly diverge in terms of the emphasis of each stage. For instance, whereas the customer decision process model beings with problem recognion t and ends with choice, the transaction process model developed by Liang and Huang (1998) beings with searching for relevant product/services and ends with post-service. An important lesson to learn from this work is that the purpose of and stage models and stages is not to capture truth in a realist sense (Tsohou et al., 2019); rather, they it is useful to think of stages as theoretical constructs that assist us in conceptualizing the studied phenomenon in a particular way. Stage models are a potentially important approach to modeling change and seem to be independent of major "-isms" in IS, such as positivism vs. interpretivism (Siponen & Tsohou, 2018), while allowing a diversity of methodological orientations (Siponen & Klaavuniemi, 2020).

4. Conclusions

TP Liang was a seminal figure in IS and his contributions to the development of IS research in the Pacific Asia region are particularly profound. His research has contributed to many domains and we reviewed three important themes of his research in this paper: electronic, mobile, and crowd commerce. Possible extensions of his research in these three themes are also highlighted for others to continue his research streams. We then moved on to discuss stage models, proffering TP Liang as an important contributor to stage model philosophy in IS. We deem TP Liang's view on stage models undervalued as they seem promising for modeling change. To illustrate the importance of stage models, we compared stage models with variance and process models in IS and showed that stage models have the potential to become a key approach to modeling dynamism and change. We hope others will continue to pursue his research ideas related to stage models.

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Appendix: Overview of Selected Articles on e-Commerce

Theme 1: Electronic Commerce						
Article	**Research approach**	**Context**	**Theoretical framework**	**Explanation (IVs, Med Vs, Mod Vs)**	**Outcome (DV)**	**Key findings / insights**
(Liang et al., 1998)	Survey (SEM)	Online shopping (e-stores)	TCT	**IVs:** Uncertainty / asset specificity / transaction costs **MedV:** Transaction costs	Customer acceptance (i.e., the marketability of products online)	In this article, the authors adopted a seven-stage model to conceptualize the transaction process (namely, 1. Search, 2. Comparison, 3. Examination, 4. Negotiation, 5. Order and payment, 6. Delivery, and 7. Post-service). These stages are used merely to operationalize different types of costs. The main findings indicate that (1) different products have different customer acceptance rates on the electronic market; (2) the web shopping experience matters immensely—experienced shoppers are concerned more about the uncertainty in electronic shopping, whereas inexperienced shoppers are concerned with both uncertainty and asset specificity; and (3) the transaction cost model is confirmed by the data, meaning that the customer acceptance decision is affected by the transaction cost, whereas the transaction cost is affected by uncertainty and asset specificity.
(Liang & Doong, 2000)	Hypothetical experimental design	Online shopping (and bargaining agents in e-stores)	1. BT 2. TT 3. PT	**IV:** Bargaining strategy **ModVs:** Cognitive style / computer efficacy / gender	Online shopping decision (via bargaining gains, bargaining satisfaction, and bargaining interaction)	In this article, bargaining is conceptualized as a search behavior, in that the two transacting parties (i.e., the negotiators) are jointly searching in a multidimensional space to find an agreed point, or what the authors refer to as “the zone of agreement.” This zone of agreement is the area in which both the seller (who wants to obtain more money) and the buyer (who wants to pay less) meet and agree on a price. The key findings suggest that (1) financial gains may not be the only reason for electronic bargaining—this insight supports the argument that bargaining may be motivated by nonfinancial reasons, such as fun, and playfulness; (2) different bargaining strategies often result in different bargaining gains, satisfaction, and interactions; and (3) the impact of the bargaining strategy on the shopping decision is mediated by differences in individual shoppers.
(Liang & Lai, 2002)	Experimental design on existing bookstores	Online shopping (e-stores)	CCM	**IVs:** Hygiene factors / motivators / media richness **MedVs:** Design quality	Consumer choice (via current purchase, future purchase, and future visit)	The consumer choice model (also known as EKB) adopted in this article divides consumer decision processes into five stages: (1) problem recognition, (2) search for information, (3) evaluation of alternatives, (4) choice, and (5) outcome evaluation. The authors also propose a 6th stage, called “the online transaction” (p. 433). The key findings suggest that e-commerce consumers are more likely to shop at well-designed websites. Among the important online platform functions, the support of transaction and post-sales services plays a key role. Hygiene factors (such as security) are critical when

						consumers decide whether to shop electronically, while motivational factors (e.g., ease of signing up) are essential when consumers choose among different electronic stores. Media richness factors are, in general, the least important.
(Liang et al., 2006)	Experimental design	Online news consumption (and using recommender systems)	1. IOT 2. UGT 3. UIT	**IVs:** Recommendation accuracy / individual motivation / user participation in giving feedback **MedV**: Recommendation accuracy	User satisfaction	The key findings indicate that (1) personalized services can increase user satisfaction through accurate recommendations of relevant content; (2) information overload theory provides important insights into user satisfaction—it was found that both the number of items recommended to the user and the recommendation accuracy had significant effects on the satisfaction of the user; (3) user satisfaction with personalized services differs significantly for users with different motivations: satisfaction was higher when the motivation was social interaction and lower when the motivation was escape or entertainment; and (4) the role of user feedback in personalized services is not significant.
(Ho et al., 2007)	OLS regression on archival data	B2C e-commerce at the cross-country level	Growth models: 1. EGT 2. XGT 3. Mixed EGT-XGT model	**IVs:** Internet penetration / telecommunications investment intensity / venture capital and credit card availability / education level	Growth in (B2C) e-commerce (in revenue)	The article tests three models that explain growth in e-commerce, described as follows. In Model I (the endogenous growth model), the results show that Internet user penetration, telecommunications investment intensity, and education levels within a country have significant impacts on a country's B2C e-commerce revenue growth. In Model II (the exogenous growth model), the results show five significant external determinants: (1) the extent of Internet user penetration in a country, (2) the intensity of telecommunications investment, (3) the availability of venture capital, (4) the education level, and (5) the degree of credit card penetration in the economy. In Model III (the mixed endogenous–exogenous model), the results suggest that B2C e-commerce growth within a country is driven by both internal and external factors associated with other leading countries. Thus, the authors argued that this model yields exploratory evidence that there may be regional contagion effects associated with other countries' e-commerce growth.
(Liang et al., 2008)	Software development and evaluation	Online library (and its recommender system for its users)	Personalization literature and relevant models	**IVs:** Recommendation mechanism / algorithm (semantic-expansion vs. keyword search)	Recommender system performance	In order to evaluate whether the semantic-expansion approach proposed in this article can improve the performance of recommendation systems, a prototype system was developed and an experiment was conducted in a computer lab. The experimental results showed that the content recommended by the semantic-expansion approach captured user interests better than the ordinary keyword approach.

Theme 2: Mobile Commerce						
Article	**Research approach**	**Context**	**Theoretical framework**	**Explanation (IVs, Med Vs, Mod Vs)**	**Outcome (DV)**	**Key findings / insights**
(Liang & Wei, 2004)	Conceptual framework	Mobile commerce	Fit-viability framework	n/a	n/a	In this special issue introduction, the authors proposed a fit-viability framework for assessing the likelihood of success or failure of m-commerce applications. For fit, criteria for measurement are identified based on task-technology fit theory. The key value-adding attributes for m-commerce are ubiquity, convenience, instant connectivity, personalization, and localization. For viability, financial and managerial criteria are identified, including three aspects: economic, organizational, and societal.
(Tsang et al., 2004)	Survey (SEM)	Mobile marketing (via SMS)	TRA	**IVs:** Entertainment / informativeness / irritation / credibility	(1) Attitude toward advertising (2) Advertising value	The results of a survey indicate that (1) consumers generally have negative attitudes toward mobile advertising unless they have specifically consented to it and (2) there is a direct relationship between consumer attitudes and consumer behavior. Thus, the article argued that it is not a good idea to send SMS advertisements to potential customers without prior permission.
(Liang & Yeh, 2011)	Hypothetical scenario survey (SEM)	Mobile commerce (mobile games)	1. TAM 2. TRA 3. Playfulness 4. Context	**IVs:** Playfulness / attitude / ease of use /subjective norms **MedVs:** Attitude **ModVs:** Context (via: task and use place)	Continuance intention	The results indicate that when context is not taken into account, (a) the user's attitude had great effects on the continuance intention to play mobile games, (b) perceived EOU had no significant influence on the user's attitude toward playing mobile games but had a direct effect on the intention to play, and (c) perceived EOU increased perceived playfulness, which in turn had significant influence on users' attitude toward playing mobile games. When the contextual factors were taken into account, the findings revealed that these factors do have an impact on the formation of users' attitudes and playing intentions. For instance, when users were free (i.e., had no other obligation or task at hand), their intention to play mobile games was determined primarily by personal attitude and subjective norms (i.e., perception of whether reference groups agreed on playing games). By contrast, when they played the mobile game under the pressure of being busy (i.e., having another obligation or task to complete), their intention to play the game was dominated solely by personal attitude, while subjective norms lost their effect. These findings suggest that service providers need to take into account the impact of use contexts and the needs of specific users when designing mobile services.
(Liang, Ling, Yeh, & Lin, 2013)	Survey (SEM)	Mobile services	1. TPB 2. TTF	**IVs:** Fit (task characteristics & technology characteristics) **MedV:** Attitude / subjective	Continuance intention	The main findings suggest that (1) a higher degree of TTF resulted in a more positive attitude toward using a mobile service; (2) perceived behavioral control had a positive effect on users' intention to use communication, entertainment, and data application services; (3) social

				norms / perceived behavioral control		norms affected the intention to use only in transaction-related applications; and (4) contextual factors had moderating effects on the intention to use.
(Liang et al., 2015)	Quantified sentiment analysis in textual reviews	iOS mobile apps	Product vs. service quality	**IVs:** Sentiment of comments (eWOM) on product quality / sentiment of comments (eWOM) on service quality.	Mobile app sales	Using a data set from the iOS app store in Taiwan, the study found that consumer reviews have a significant influence on app sales rankings. The study also showed that app users care about both service quality and product quality, especially for free apps. Further, the authors acknowledged the possibility that the effects of eWOM on sales vary across regions and mobile platforms. For instance, it is possible that Android apps might show characteristics that differ from iOS apps.
Theme 3: Crowd Commerce						
Article	**Research approach**	**Context**	**Theoretical framework**	**Explanation (IVs, Med Vs, Mod Vs)**	**Outcome (DV)**	**Key findings / insights**
(Liang & Turban, 2011)	Conceptual framework	Social commerce sites	n/a	n/a	n/a	The purpose of this introduction article was to present a framework that integrates several elements in social commerce research and to summarize the papers included in this special issue. The proposed framework includes six key elements for classifying social commerce research: (1) research theme, (2) social media, (3) commercial activities, (4) underlying theories, (5) outcomes, and (6) research methods.
(Liang et al., 2011)	Survey (SEM)	Social commerce (Plurk.com, a microblogging website)	Combines social support theory (SST), IS success model, TRA, TPB, and social exchange theory (SET)	**IVs:** Social support (emotional and informational support) / website quality (system and service quality) **MedV:** Relationship quality (trust, satisfaction, and commitment)	(a) Social commerce intention (b) Loyalty	The study investigates how social factors, such as social support and relationship quality, affect the user's intention of future participation in social commerce. The results indicate that (1) social support and website quality positively influence the user's intention to use social commerce and their loyalty to the social networking site and that (2) these effects are mediated by the quality of the relationship between the user and the social networking site.
(Chiu et al., 2014)	Conceptual framework	Crowdsourcing	Herbert Simon's decision process model	n/a	n/a	The article introduces Simon's decision process model, which includes three major phases before implementation: **(1) intelligence** (information gathering and sharing for the purpose of problem solving or opportunity exploitation, problem identification, and the determination of the problem's importance), **(2) design** (generating ideas and alternative solutions), and **(3) choice** (evaluating the generated alternatives and then recommending or selecting the best course of action). Building on this model, the authors pointed out that crowdsourcing can provide different types of support to the managerial decision-making process beyond the typical applications in the design (e.g., idea generation and co-creation) and choice (e.g., voting) phases. Further, the article provides a two-dimensional framework to organize crowdsourcing research that includes **four components** (task, crowd,

						process, and evaluation) and **three levels** (managerial, behavioral, and technical).
(Liang et al., 2019)	Hypothetical experiment using real fundraising cases	Crowdfunding	1. CAM 2. ELM 3. Trust	**IVs:** Project information quality / fundraiser expertise / fundraiser reputation / value similarity / funder's disposition to trust **MedV:** Funder's trust	Investment intention (and behavior)	The main findings suggest that (1) trust is a significant determinant of crowdfunding investment intention, which is highly correlated with the actual project success. The authors note that this is similar to online purchasing when customers decide whether it is worth buying a certain product or service; (2) cognition-based trust factors were found to have significant effects on potential funders' trust—fundraisers' ability/expertise had the largest effect size, while project information quality was the second highest; (3) the ELM suggested that cognitive cues via the central route are an effective approach to attitude persuasion; and (4) funder's personal disposition to trust did not play a role in trust formation.
(Liang et al., 2021)	Hypothetical scenario & survey (SEM)	Sharing platforms	1. VAM 2. TCT	**IVs:** Uncertainty (asset specificity / transaction costs) / economic benefit / non-economic benefit **MedV:** Perceived value **ModV:** Product type	Intention to adopt sharing platforms	The main findings suggest that perceived value predicts well the intention to use a sharing platform. In other words, users with a higher perceived value of a sharing platform are more likely to utilize said platform. Further, perceived value can be increased by reducing transaction costs and increasing perceived benefits. Finally, it was also revealed that transaction costs are positively associated with perceived uncertainty and, at the same time, are negatively associated with perceived asset specificity.
Abbreviations used in this table: BT = Bargaining Theory; CAM = Cognitive Affective Model; CCM = Consumer Choice Model; EGT = Endogenous Growth Theory; XGT = Exogenous Growth Theory; ELM = Elaboration Likelihood Model; IOT = Information Overload Theory; PT = Prospect Theory; TAM = Technology Acceptance Model; TCT = Transaction Cost Theory; TPB = Theory of Planned Behavior; TRA = Theory of Reasoned Action; TT = Transaction Theory; TTF = Task-Technology Fit; UGT = Uses and Gratification Theory; UIT = User Involvement Theory; VAM = Value-based Adoption Model.						