Why do Tourists Accept Lodging Through Accommodation Sharing Platforms? Model Development and Model Comparison

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DEDICATION

To my wife and two daughters, and my parents, we experienced the COVID-19 pandemic from 2019 to 2021 together.

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ABSTRACT

The P2P accommodation sharing market has emerged as a disruptive innovation as it has exponentially expanded globally, even though this market is still emerging and has not been used by most people. This study investigates why tourists accept the sharing platforms and how to promote this service. A literature review on innovation adoption models was conducted to select a proper theoretical framework to investigate travelers' motivation for using Airbnb. According to model-evaluation principles and literature analysis, this self-efficacy-based value adoption model (SVM) was selected, which is derived from social cognitive theory's reciprocal determination. Based on the SVM, an extended SVM (ESVM, also called human-product-adoption model, HPAM) was developed to include constructs of general personal innovativeness (GPI), self-efficacy (SE), perceived value (PV), platform trust (PT), and intention (IN). A representative consumer sample was drawn through Ipsos in three typical Chinese cities. The measurement model was first examined to guarantee the constructs' reliability and validity. The structural model test results supported all the hypotheses. Personal factors such as GPI and SE influence the service's factors such as PV and PT, and all of them impact the users' intention to use Airbnb. The explanatory power of the ESVM on IN (67%), PT (66%), PV (48%), and SE (54%) indicated the model's good predictive power. To demonstrate that SVM is a more superior theoretical model, a comparative study between SVM and the classic technology acceptance model (TAM) was conducted. All fit indices appeared to favor SVM over TAM. The significance of this research in theory building and practical implications are discussed at the end of this report.

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CHAPTER 1
INTRODUCTION

1.1 THE RESEARCH BACKGROUND

Airbnb and similar services are third-party platforms through which users seek short-term accommodation from people who want to rent their spare houses or rooms (Ert et al., 2016). Airbnb is seen as a typical Internet-based sharing economy known as collaborative consumption or peer-to-peer (P2P) accommodation (Lee & Kim, 2019; Boateng, Kosiba & Okoe, 2019). Since Airbnb was launched in 2008, lodging through home-sharing platforms has been increasingly acknowledged by travelers worldwide (Guttentag, 2015). The number of Airbnb users has been growing exponentially, and estimates suggest there is still a huge market space in the future, especially in emerging markets such as China (Ert et al., 2016; Qin et al., 2020).

In mainland China, services like Uber have been bringing a dramatic change in urban transportation, Airbnb and similar services are forming another round of "sharing economy" storms in the hospitality and tourism industry (Zhu et al., 2017). By lodging through home-sharing websites including Airbnb.com and Chinese sites like Mayi.com and Xiaozhu.com, the 2019 revenue of the shared accommodation market increased to 22.5 billion yuan (about $3.4 billion) (China Internet Network Information Center, 2020). This was 5.8 times higher than in 2016 and accounted for 7.3% of the total revenue of the Chinese hospitality market. According to the Annual Report on China's Sharing Economic Development (2020) issued by the State Information Center in China, more than 90% of the Internet users have never used home-sharing platforms. A few articles have explored the factors that influence people to use Airbnb in western countries (e.g., U.S.) (Mao & Lyu, 2017; So, Oh & Min, 2018; Chen & Chang, 2018; Liang, Choi & Joppe, 2018; Tussyadiah & Pesonen, 2018). However, little research has investigated the factors that influence Chinese consumers to adopt home-sharing. Considering the differences in government regulation, economic development, and social cultures, findings from the western world may not be fully applicable to marketing in China and therefore it is necessary to understand Chinese consumers' psychology and behavioral intention to use home-sharing platforms.

1.2 THE OBJECTIVES OF THE STUDY

This study uses the sharing economy platform of Airbnb to explore why Chinese tourists adopt or do not adopt this disruptive innovation by examining, comparing, and developing several user adoption models. The theoretical and empirical research objectives follow.

1) This study will review literature on existing innovation adoption models, analyze these models, and determine if the self-efficacy value model (SVM) is a better theoretical framework to analyze consumer adoption innovation than the classic technology acceptance model (TAM).
2) Based on the framework of SVM and the characteristics of accommodation sharing platforms, an extended SVM (ESVM) will be developed to investigate the reasons why tourists use Airbnb, including personal factors (like innovativeness and self-efficacy) and product factors (like perceived value and platform trust).
3) This study will examine the developed model ESVM with an empirical survey in China and whether SVM is superior to TAM in explaining consumers' intentions to adopt home-sharing platforms using an identical model structure,

the same research objective, and a representative sample.

1.3 THE ORGANIZATION OF THE THESIS

Chapter 2 will present a literature review and analysis to evaluate the models employed in this study. Chapter 3 establishes an extended SVM model with constructs and hypotheses. Chapter 4 describes the research methodology and data collection procedure. The results and discussion are reported in chapter 5. Chapter 6 draws final conclusions.

CHAPTER 2

LITERATURE REVIEW AND MODEL DEVELOPMENT

Based on a literature review and a brief statistical analysis of innovation adoption models, a proper theoretical framework was selected to develop the model to explain why tourists adopt accommodation sharing platforms. The theory building and model assessment are introduced in this section.

2.1 LITERATURE REVIEW ON INNOVATION ADOPTION MODELS

Recently, a few articles have explored reasons why tourists choose Airbnb or another home-sharing mode. Possible reasons are: attitudes regarding motivations and constraints (So et al., 2018); perceived value and satisfaction (Chen & Chang, 2018); trust in the photographs of hosts' residences (Ert et al., 2016); attitude, subjective norms, electronic word-of-mouth (eWOM); experience expectation and familiarity (Mao & Lyu, 2017); price sensitivity; perceived value and risk (Liang et al., 2018). Some attributes of Airbnb have been revealed, such as perceived value, trust, and risk. However, these studies have failed to consider how users see themselves (self-perception factors such as self-efficacy and innovativeness). They also did not consider how user self-perception affects their perceptions of Airbnb and their behavioral intentions.

In the broader context of innovation adoption research, consumers' perceptions of themselves are often ignored or receive insignificant attention. Table 2.1 summarizes a literature review of innovation adoption and the latest studies in order to compare different models and results.

Table 2.1 Literature review of innovation acceptance models

Author(s)	Object	Model(s)	Antecedents of Intention (R^2/Adjusted R^2)
Davis et al. (1989)	Information System	TAM	PU, PEOU →IN (0.47)
Taylor & Todd (1995)	Computer Resource Center	TAM	PU, AT →IN (0.52)
		TPB	AT, SN, PBC →IN (0.57)
		Decomposed TPB	AT, SN, PBC →IN (0.60)
Venkatesh & Davis (2000)	Information System	TAM2	PU, PEOU, SN →IN (0.49)
Riemenschneider at al. (2002)	Methodologies of software development	TAM	PU, PEOU →IN (0.50)
		TAM2	PU, PEOU, SN, Vol →IN (0.58)
		PCI (Perceived characteristics of innovating)	RA (=PU), Complexity(ns), Vol, Comp, Result Demonstrability (ns) Visibility (ns) →IN (0.58)
		TPB	AT(=PU), SN, PBC (ns) →IN (0.55)
		MPCU	Job Fit(=PU), Complexity (ns), Social factors(=SN), FC (ns), Career Consequences (ns) →IN (0.55)
Venkatesh et al. (2003)	Information Technology	UTAUT (direct effects only)	PE, EE, SI →IN (0.30)
		UTAUT (direct effects & interaction items)	PE EE, SI, and moderators (age, gender, experience, and voluntary) →IN (0.70)
		TAM2	PU, PEOU, SN →IN (0.38)

		MM	EM, IM →IN (0.37)
		TRA	AT, SN →IN (0.30) (R^2 from voluntary setting and first time, same as the following seven models)
		TPB	AT, SN, PBC →IN (0.37)
		TAM+TPB	PU, AT, SN, PBC →IN (0.39)
		MPCU	Job-fit, Complexity, Long-term consequences, Affect toward use, Social factors, FC →IN (0.37)
		IDT	RA, PEOU, Result demonstrability, Trialability, Visibility, Image, CO, Voluntariness →IN (0.38)
		SCT	OE, SE, Affect, Anxiety → IN (0.37)
Van der Heijden (2004)	Information System	Extended TAM	PU, PEOU, EN →IN (0.35)
Hong et al. (2006)	Continued IT	TAM	PU, PEOU →IN (0.63)
		ECM	PU, Confirmation, ST →IN (0.50)
		Extended ECM	PU, PEOU, ST →IN (0.67)
Kim et al. (2007)	Mobile Internet	TAM	PU, PEOU →IN (0.13)
		VAM	PV →IN (0.36)
Kleijnen et al. (2007)	Mobile Channel	VAM	PV →IN (0.39)
Kim et al. (2008)	E-commerce		FM, PR, TR, Benefit →IN (0.34)
Hsu & Lin (2008)	Blog	TRA	AT, SI (ns), Community Identification →IN (0.83)

Zhu et al. (2010)	Mobile App	SVAM	(PV, PC, SE) →AT →IN (0.72)
Han & Kim (2010)	Green Hotel	TRA TPB Extended TPB	AT, SN →IN (0.52) AT, SN, PBC →IN (0.56) AT, SN, PBC, ST, Overall Image, Frequency of Past Behavior →IN (0.72)
Venkatesh et al. (2012)	Mobile Internet	UTAUT (D) UTAUT (D+I) UTAUT2 (D) UTAUT2 (D+I)	PE, EE, SI →IN (0.35) PE EE, SI, and moderators (age, gender and experience) →IN (0.55) PE, EE, SI, FC, Hedonic Motivation, Price Value, Habit →IN (0.44) PE, EE, SI, FC, Hedonic Motivation, Price Value, Habit, and moderators (age, gender and experience) →IN (0.73)
Amaro & Duarte (2015)	Online Travel Agency	TAM+TPB+ IDT	AT, PBC, Comp, TR, PR, RA (ns), Communicability (ns) →IN (0.67)
Ponte et al. (2015)	Online Travel Websites	Extended VAM	PV, TR →IN (0.68)
Agag & El-Masry (2016)	Online Travel Communities	TAM+IDT	Intention to participate, AT, TR →IN (0.78)
Pengnate & Sarathy (2017)	Rental website	Extended TAM	PU, PEOU, TR →IN (0.59)
Rahman et al. (2017)	Advanced Driver Assistance Systems	TAM UTAUT TPB	PU, PEOU →IN (0.73) PE, EE, SI →IN (0.71) AT, SN, PBC →IN (0.80)

Zhu et al. (2017)	Ride-sharing App	SVM	PV, AT, SE (ns) →IN (0.59)
Liu & Mattila (2017)	Airbnb	Experimental design	Interaction effect of advertising appeal (belongingness vs. uniqueness) and sense of power (low vs. high) on purchase intention
Mao & Lyu (2017)	Airbnb	Extended TPB	AT, SN, FM, eWOM, Unique Experience Expectation →IN (0.71)
Hong et al. (2017)	Smartwatch	Decomposed VAM	(Innovativeness →) Hedonic Value, Utilitarian Value →IN (0.48)
Hur et al. (2017)	Mobile App	Extended TAM	(Innovativeness →) PU, PEOU, Perceived Playfulness →IN (N/A)
Buckley et al. (2018)	Automated vehicles	TAM TPB	PU, PEOU →IN (0.41) AT, SN, PBC →IN (0.46)
So et al. (2018)	Airbnb	Extended TPB	AT, PBC, SI, EN, Trend Affinity, Insecurity →IN (0.71)
Chen & Chang (2018)	Airbnb	Extended VAM	PV, ST, Rating Volume →IN (0.47)
Liang et al. (2018)	Airbnb	Prospect theory and means-end chain (MEC)	PR, PV, Price Sensitivity, eWOM, Perceived Authenticity (ns) →IN (N/A)
Min et al. (2018)	Uber	IDT+TAM	AT →IN (0.30)
Tussyadiah & Pesonen (2018)	P2P Accommodation	--	Drivers (social & economic appeals); Barriers (TR, FM, efficacy, cost) →IN (N/A)
Wang & Jeong	Airbnb	IDT+TAM	(PI →(PEOU, PU, TR) →)

(2018)			AT, (Amenities, Host-gust relationship →) Satisfaction →IN (0.60)
Lee et al. (2018)	Uber	Extended VAM	PR, TR, Perceived Benefits →IN (0.51)
Kong et al. (2020)	Airbnb	--	Social referrals, Information quality, Transaction Safety →Trust →Continuance use of Airbnb & Positive WOM
Zhu et al. (2020)	Autonomous vehicle	MPAM	SM, MM →SN, SE (→), PU, PR →IN (0.54; 0.34)
Du et al. (2021)	Self-driving Car	--	MM →SN, SE, TR →IN (0.58)
Jung et al. (2021)	Airbnb	Extended TAM	TR, PEOU, Interactivity →PU →IN (N/A)
Zhu et al. (2021)	Free-floating Car Sharing	Decomposed SVAM	PV, SE →IN (0.66)

Note： ECM (Expectation-Confirmation Model), IDT (Innovation Diffusion Theory), MM (Motivational Model), MPCU (Model of PC Utilization), SCT (Social Cognitive Theory), TRA (Theory of Reasoned Action), TAM (Technology Acceptance Model), TPB (Theory of Planned Behavior), UTAUT (Unified Theory of Acceptance and Use of Technology), VAM (Value Adoption Model), MPAM (Media-based Perception and Adoption Model), SVAM (Self-efficacy-based Value Adoption Model); AT (Attitude), CO (Compatibility), D (direct effects only), D+I (direct effects and interaction terms), EE (Effort Expectancy); EM (Extrinsic Motivation), EN (Enjoyment), eWOM (electronic Word of Mouth), FC (Facilitating conditions), FM (Familiarity), IM (Intrinsic Motivation), IN (Intention), MM (Mass Media), OE (Outcome expectations), PBC (Perceived Behavior Control), PE (Performance Expectancy), PEOU (Perceived Ease of Use), PR (Perceived Risk), PU (Perceived Usefulness), PV (Perceived Value), RA (Relative Advantage), SE (Self-efficacy), SI (Social Influence), SN (Subjective Norm), ST (Satisfactory), SM (Social Media), TR (Trust); ns (not significant), N/A (not available).

2.2 A BRIEF ANALYSIS ON ADOPTION MODELS

Numerous studies on innovation adoption have been applied to different technologies or groups in the past decades (Samaradiwakara & Gunawardena, 2014). These include TAM (technology acceptance model, Davis et al., 1989), TPB (theory of planning behavior, Taylor & Todd, 1995), and UTAUT (unified theory of acceptance and use of technology, Venkatesh et al., 2003). With only two constructs of perceived usefulness (PU) and perceived ease of use (PEOU), as shown in Figure 2.1, TAM is one of the most commonly-used models in a diverse set of IT for its parsimony (Alalwan et al., 2016; Hong et al., 2006; Lassar et al., 2005; Scherer et al., 2019; Venkatesh and Davis, 2000).

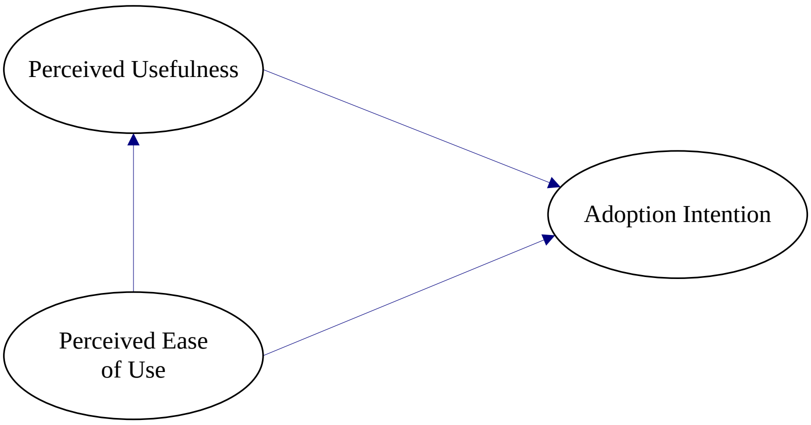

Figure 2.1 Technology Acceptance Model (TAM) (Davis et al., 1989)

TAM is often used as a benchmark when researchers develop new models such as TPB and UTAUT (Hong et al., 2006; Taylor & Todd, 1995; Venkatesh et al., 2003). Because the explanatory power of TAM is limited by its parsimonious structure (Sun & Zhang, 2006), a variety of extended TAM models were developed (Alalwan et al., 2016; Amaro & Duarte; 2015; Featherman & Pavlou, 2003; Hong et al., 2006; Hur et al., 2017; Lu et al., 2014; Scherer et al., 2019; Venkatesh & Davis, 2000). On the other hand, the addition of variables and patchwork models might have bloated the model and weakened its parsimony.

Figure 2.2 summarizes some external metrics and internal criteria of how to evaluate or build a model.

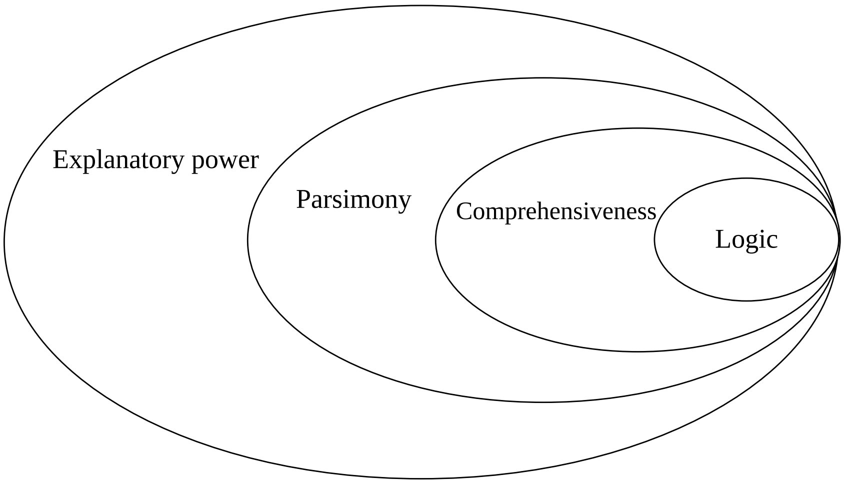

Figure 2.2 Model assessment criteria

Explanatory power and parsimony are two measurable indicators to assess a model (Hong et al., 2006; Shmueli, 2010), and are similar to usefulness and ease of use in TAM. However, explanatory power and parsimony generally conflict with each other for a model. A relatively complex model structure contributes to producing a less rigorous theoretical model that paradoxically produces better fit indices (Hooper et al., 2008). By a statistical analysis of literature in Table 2.1, a simple linear regression analysis demonstrates a significant positive relationship (with a standardized coefficient of 0.56 with the p-value of 0.003) between the number of antecedents and the value of explained variance R^2. It can be understood as a multiple regression equation. Each time an independent variable is added, the dependent variable's explanatory degree will improve (Hernandez, & Mazzon, 2007). Besides R^2 and the number of antecedents, information criterion fit indices (like AIC and BIC) and the parsimonious fit indices (like PGFI and PNFI) can also be adopted to compare and evaluate a model's explanatory power and parsimony (Schreiber, 2017). However, for two specific models with different independents, we cannot predicate that the explanation power of a model with more antecedents must be higher than another one because explanatory power depends not only on the number of precedents but also on the model's quality with its precedents.

Comprehensiveness (not completeness) and logic are two internal criteria for evaluating a model, especially the extent to which the construct is "right" (Whetten, 1989). A model (or theory) is a statement of constructs (or conceptions) and their relationships that show how and why a phenomenon occurs (Corley & Gioia, 2011). Accordingly, appropriate construct selection together with a relationship hypothesis is essential for model development. Although quantitative indicators are inadequate to measure comprehensiveness and logicality, comparative studies in the same context can provide some specific clues (see Buckley et al., 2018; Hong et al., 2006; Rahman et al., 2017; Riemenschneider et al., 2002; Taylor & Todd, 1995; Venkatesh et al., 2003, 2012). Extended models (such as extended TAM and TPB) explain better because more perspectives are considered even though parsimony is sacrificed. The comparative study of VAM (value adoption model) and TAM might be an extraordinary example that VAM with perceived value (PV) explains more variance in a more parsimonious structure than TAM with PU and PEOU (Kim et al., 2007). Perceived value as the ratio of benefits and costs is a better concept than perceived usefulness and ease of use, at least in the mobile Internet setting.

Furthermore, logic is the core of a theory. For consumer research, logic is not represented by mathematical or symbolic types, as Wacker (1998) mentioned, but rather by the assumption of relationships among constructs that are inherently consistent and rational (or falsifiable) in some settings. Most innovation adoption models in Table 2.1 were developed logically with different perspectives and priorities. For example, TAM emphasizes the perceived process (ease of use) and effect of using IT innovation in an organizational environment with constructs PEOU and PU regardless of user's monetary costs and personal preferences. TPB introduces users' self-perceptions involving constructs of attitude, social norms, and perceived behavior control. VAM focuses on the perceived value of the innovation.

From perspectives of comprehensiveness and logic, the self-efficacy-based value adoption model (SVAM or SVM) developed by Zhu et al. (2010) is a proper theoretical framework derived from social cognitive theory because it emphasizes both the influence of the product and user together on the behavior with reasonable logical relationships, as shown in Figure 2.3.

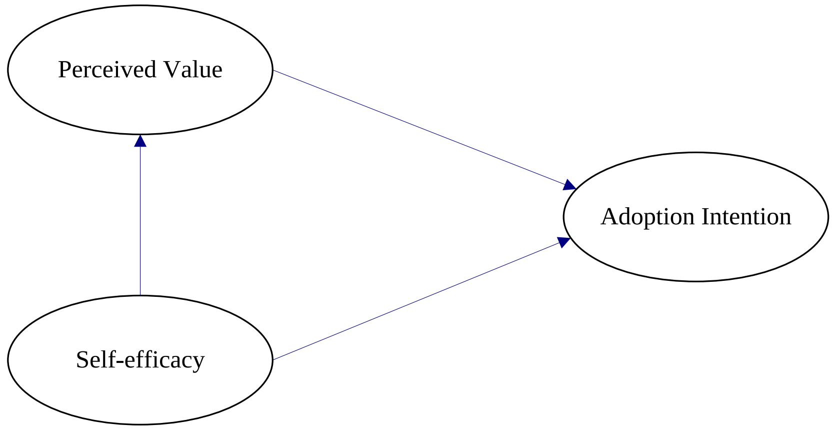

Figure 2.3 Self-efficacy-based Value Model (SVM) (Zhu et al., 2010)

As an antecedent of intention, self-efficacy represents one's belief in his/her capability to use a specific innovation. Perceived value is the overall perception of the new product or service's benefits and costs, which are more comprehensive constructs than PEOU and PU in TAM, respectively. SVM has been validated as a successful model to explain users' adoption intention (Zhu et al., 2017; 2021). However, the evidence of empirical research is limited, and no comparative research has proven that SVM is a better model. In terms of the similar logical relationships and the same parsimonious structure of TAM and SVM as shown in Figure 2.1 and Figure 2.3, rigorous comparative study would be required to examine SVM and TAM's performance to explain consumer adoption intention of Airbnb.

2.3 MODEL DEVELOPMENT

Social cognitive theory (SCT) is one of the most influential human behavior theories (Bandura, 1986; Venkatesh et al., 2003). To study the use of and training on computer technologies, Compeau and Higgins (1995) applied two concepts of SCT (the cognitive influence on behavior and self-efficacy) to develop a technology acceptance model. This model includes constructs of performance outcome expectations, personal outcome expectations, computer self-efficacy, affect, and anxiety, which Venkatesh et al. (2003) called the SCT model. Unlike the above SCT model, Zhu et al. (2010, 2017) developed the SVM model by adapting the triadic reciprocal causation of human being, environment, and behavior to explore the relationships among user, product, and intention (see Figure 2.4).

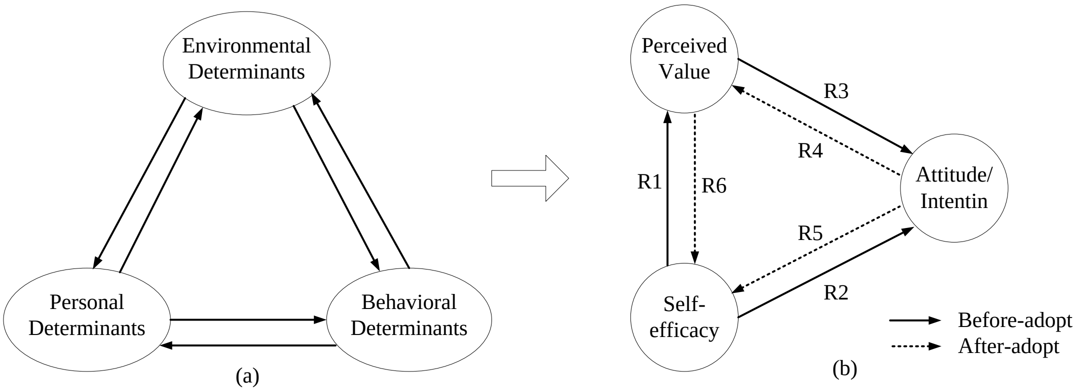

Figure 2.4 The model development of SVM from SCT (Zhu et al., 2010; 2017)

This study will consider internal logic, comprehensiveness, parsimony, and explanatory power, and employ SVM to explore the tourists’ motivation to adopt Airbnb in China. SVM and TAM will also be studied to demonstrate the superiority of SVM.

Most importantly, this study developed an extended SVM (ESVM) to explore other possible personal and product-related factors that influence users to accept accommodation sharing. Previous SVM studies used the value-based adoption model (Kim et al., 2007), and focused on value dimensions of innovation: functional, emotional, social, and other negative values (Zhu et al., 2010; 2017). The formation of self-efficacy and perceived value also have been explored from multiple dimensions in a decomposed VSM (Zhu et al., 2021). However, more personal and product constructs might need to be investigated according to consumer and product characteristics, such as general personal innovativeness and platform trust in accommodation sharing (Parks & Guay, 2009).

Unlike traditional hotels with standard products and established brands, hosts in Airbnb provide localized and personalized accommodation by relying on third-party platforms. The novel elements and curious expectations undoubtedly attract innovative travelers (Beldona et al., 2012). Innovation is often accompanied by risk and trust. Therefore, general personal innovativeness and platform trust will be included as human-related and product-related determinants in this study. In retrospect, this study is consistent with the recent empirical research on innovative applications with the construct of innovativeness (Hong et al., 2017; Hur et al., 2017) and sharing economy with the construct of trust (Kong et al., 2020; Lee et al., 2018; Pengnate & Sarathy 2017; Wang & Jeong, 2018).

After allowing for the innovative characteristics of the home-sharing mode, therefore, this study expands the parsimonious SVM to a human-product-adoption model (HPAM), which is shown in Figure 2.5. In the theoretical framework, general personal innovativeness and perceived value are two primary determinants that influence secondary determinants of self-efficacy and platform trust. Human-related determinants are hypothesized to influence product-related environmental determinants, and these two constructs impact adoption-related determinants. The next part of this study on Airbnb defines each construct and specializes every hypothesis to formulate a rationale for the model's causal relationships.

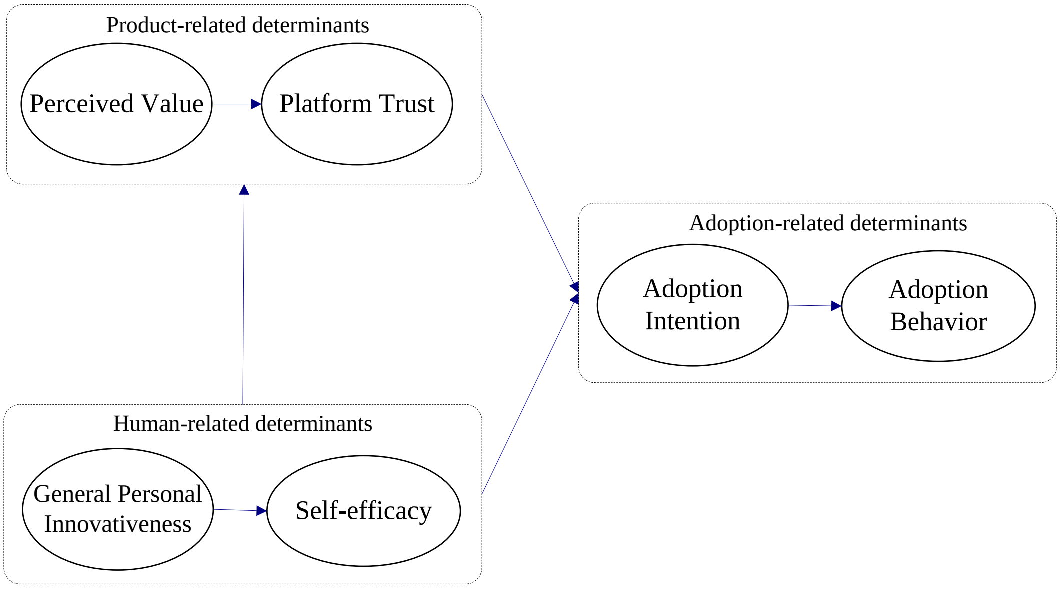

Figure 2.5 The conceptual framework of human-product-adoption model (HPAM)

CHAPTER 3
CONSTRUCTS AND HYPOTHESES

Guided by the HPAM framework, this section proposes the hypotheses and relationships of the extended SVM (ESVM) model with constructs of general personal innovativeness (GPI), self-efficacy (SE), perceived value (PV), platform trust (PT) and adoption intention (IN). These models will be integrated with the accommodation sharing service and platform of Airbnb. Perceived usefulness (PU) and perceived ease of use (PEOU) of TAM are also defined, and the logic relationships in three models are established based on empirical evidence.

3.1 GENERAL PERSONAL INNOVATIVENESS

According to Rogers' innovation diffusion theory, innovative consumers tend to purchase earlier than most others as new products emerge (Hong et al., 2017). Personal innovativeness is an innate personality trait involving psychological elements such as curiosity, ambition, and rationality; and sociological elements such as social identification and experience (Bartels & Reinders, 2011; Hong et al., 2017; Lu, 2014). Like the concept of self-efficacy, personal innovativeness can also be divided into two primary levels: general and specific innovativeness. These were extensively applied in the research of innovation adoption and diffusion (Aldas-Manzano et al., 2009; Thakur & Srivastava, 2015). Domain-specific innovativeness is one's tendency to try innovations in a particular area like Internet-related information technology (Aldas-Manzano et al., 2009; Lu et al., 2005; Thakur & Srivastava, 2015). General personal innovativeness is defined as one's overall innovative consciousness with the willingness to attempt innovation (Lee et al., 2007; Yu et al. 2017). This concept is adopted to explore how personal traits affect people's self-image and acceptance of Airbnb.

General personal innovativeness and self-efficacy are two critical traits for individuals to adopt an innovation (Compeau & Higgins, 1995; Kwon et al., 2007; Lee et al., 2007; Thakur & Srivastava, 2015). Theoretically, innovative individuals tend to have more self-confidence when entering a new environment or beginning a new task (Agarwal & Karahanna, 2000; Thatcher & Perrewe, 2002). Thatcher and Perrewe (2002) believed that personal traits shape one's perceptions of his/her capability, and they verified that personal innovativeness impacts individuals' attitudes regarding computers and self-efficacy. Agarwal and Karahanna (2000) also verified that personal innovativeness with information technologies significantly influences one's beliefs about general and specific self-efficacy. Research conducted by Kwon et al. (2007) and Knight et al. (2011) did not find a direct causal relationship between personal innovativeness and self-efficacy, but the tables of correlation of constructs in this paper manifested a strong correlation between them. Based on this evidence, this study assumes that general personal innovativeness has a strong positive impact on the self-efficacy of lodging through home-sharing platforms.

H1: General personal innovativeness positively affects self-efficacy.

Sheer boldness and curiosity strengthen people's self-confidence in their capabilities to handle innovation, amplify the perceived benefits, and mitigate their perceived sacrifices (Lu et al., 2005; Truong, 2013). Lu et al. (2005) showed that personal innovativeness in information technology significantly increases trust in Internet services. Lowe and Alpert (2015) verified that general personal innovativeness affects consumers' utilitarian and hedonic values. Findings from Hong et al. (2017) revealed that consumer innovativeness is associated with continuance intention but mediated by hedonic value and utilitarian value. In the context of hospitality, Beldona et al. (2012) also confirmed that travelers' innovativeness has a significant impact on the perception of potential value in travel-oriented location-based marketing services. A few studies have used the TAM and demonstrated that general personal innovativeness is an essential predictor of PU and PEOU (Hur et al., 2017; Wang et al., 2017; Yu et al., 2017). In the context of home-sharing service, therefore, we hypothesize that:

H2: General personal innovativeness positively affects perceived value.

Previous research asserted that innovative consumers are more willing to experience risks and uncertainty to appreciate and embrace new information technology (Bartels & Reinders, 2011; Lee et al., 2007; Li et al., 2015; Thakur & Srivastava, 2015; Truong, 2013; Yu et al. 2017). A few empirical studies of e-commerce indicated consumer innovativeness significantly affects the trust of electronic mediated environment and online payment (Rouibah et al., 2016). Review on sharing economy research suggests that innovativeness and trust are two main study streams, but different points of view have formed in the two main streams (Cheng, 2016). Wang & Jeong (2018) have involved the logical relationship between personal innovativeness and trust in Airbnb. Therefore, it is supported to propose the following assumption.

H3: General personal innovativeness positively affects platform trust.

Literature shows that personal innovativeness in the settings of online shopping can predict adoption intention (Goldsmith, 2002), online banking (Lassar et al., 2005), and mobile payments (Thakur & Srivastava, 2015). Although Lu et al. (2005) rejected the hypothesis that personal innovativeness directly positively impacts mobile Internet services' adoption intention, Lu (2014) later evidenced that user personal innovativeness directly influences continuance intention toward mobile commerce. Research showed that innovativeness of travelers positively influences online purchase intention in rural tourism (San Martín & Herrero, 2012). Lee et al. (2007) showed that the impacts of attitude and subjective norm on online travelers' shopping intention depend primarily on online travelers' innovative predisposition. Thus, we hypothesize that consumers with greater innovativeness will more likely adopt Airbnb.

H4: General personal innovativeness positively affects adoption intention.

3.2 SELF-EFFICACY

Self-efficacy is one of the most important concepts of social cognitive theory that describes one's belief in his/her capability to perform (Bandura, 1997; Hsu & Chiu, 2004). Most self-efficacy studies have focused on a specific performance or domain, i.e., specific self-efficacy rather than general self-efficacy (Agarwal & Karahanna, 2000; Bandura, 2006; Hsu & Chiu, 2004). In the present study, self-efficacy is defined as an individual judgment of one's capability to lodge through sharing platforms, including the self-confidence of using information technologies and using the sharing accommodation. In the early research of technology acceptance, self-efficacy was adapted as a distal factor in the adoption models, for instance, as the antecedents of perceived behavior control in the TPB model (Taylor & Todd, 1995) and perceived ease of use in TAM (Venkatesh, 2000; Venkatesh et al., 2003). As the innovation adoption study progressed from the organizational setting to the consumer market, researchers paid more attention to self-efficacy, and they introduced self-efficacy as a direct determinant of intention (Compeau & Higgins, 1995; Zhu et al., 2010; 2017). In this study, the direct and indirect effects of self-efficacy on behavior will be assumed and tested extensively.

According to social cognitive theory (SCT), individuals with high self-efficacy will develop positive evaluations towards future results (Bandura, 1997). Self-efficacy of ridesharing was validated as a fundamental factor that impacts functional value, emotional value, and social value, and overall perceived value; this was consistent with another study on the adoption of m-commerce application (Zhu et al., 2010, 2017). A few additional studies explored the impact of self-efficacy on perceived value; nevertheless, some related studies partially support this relationship. For example, self-efficacy was found to strengthen the perceived usefulness (Huang & Liaw, 2005) and perceived ease of use (Kwon et al., 2007; Mun & Hwang, 2003), and to reduce perceived risk (Alalwan et al., 2016). Thus, referring to the notion of perceived value (ratio of benefits to sacrifices), we have direct and indirect evidence to propose the hypothesis:

H5: Self-efficacy positively affects perceived value.

Self-efficacy substantially impacts uncertainty reduction and trust in e-commerce transactions. Trust building is an individual's perception process, influenced by his/her judgment of ability to involve (Kim et al., 2009). Few empirical studies have examined the interaction between self-efficacy and trust even though they are deemed theoretically interdependent (Tams et al., 2018). Adopting an elaboration likelihood model, Zhou (2012) illustrated the direct and moderating effects of self-efficacy on initial trust-building in mobile banking. Proactive-motivational states, including self-efficacy, were validated to diminish uncertainty and psychological risk, and to predict proactive behaviors (Tams et al., 2018). The author believes that travelers with higher self-efficacy of lodging through home-sharing platforms are more likely to trust the sharing platforms.

H6: Self-efficacy positively affects platform trust.

As an essential factor in explaining individuals' behavioral motivations, previous research on information systems suggests that self-efficacy mediates the effects of distal factors and is a proximal driver of users' behavior (Compeau & Higgins, 1995; Tams et al., 2018). For instance, Zhu et al. (2010, 2017) empirically validated that specific self-efficacy significantly influences perceived value and behavior intention toward mobile applications. Hsu and Chiu (2004) also empirically showed that web-specific self-efficacy positively affects consumers' adoption intention to e-commerce. Few investigations exist regarding the direct impact of self-efficacy on behavior intention, but we have reasons to believe consumers with higher self-efficacy are more willing to adopt accommodation sharing services.

H7: Self-efficacy positively affects adoption intention.

3.3 PERCEIVED VALUE

Perceived value is defined as the result of a comparison of the perceived benefits (aka positive value) and sacrifices (aka negative value) by the customer according to the perception of what is received and given (Dodds et al., 1991; Kim et al., 2007; Mao & Lyu, 2017; McDougall & Levesque, 2000; Zeithaml, 1988). Perceived positive value is generally categorized into functional (or utilitarian), emotional (or hedonic), and social value (Hong et al., 2017; Sheth et al., 1991; Zhu et al., 2017). Perceived monetary costs, risks, and effort are classified as the perceived negative value of adopting an innovative product or service (Kim et al., 2007, Zhu et al., 2010). As an emerging accommodation pattern, home-sharing differs from traditional hotels by offering customers a "feeling at home" (i.e., belongingness) and an "atypical place to stay" (i.e., uniqueness) with more available locations and accessible culture (Liu & Mattila, 2017). On the other hand, attempting to lodge through home-sharing platforms also involves learning costs and various risks such as performance, security, and financial risks. Due to space limitations, this article will explore the mental transformation based on the overall value perception of accommodation sharing but not the possible dimensions of Airbnb's perceived value.

Although studies have suggested that perceived value and trust are the critical determinants of purchase intention in the field of e-commerce (Kim et al., 2008; Ponte et al., 2015; Wang & Jeong, 2018), to my limited knowledge, no research has examined the effect of perceived value on trust in a platform. A related study conducted by Agag & EI-Masry (2016) indicated that perceived usefulness builds trust in the online travel community. The higher the perceived value of home-sharing, the higher the possibility that potential travelers will trust this platform and ignore the uncertainty. This is the first study that proposes and tests the positive effect of perceived value on the platform trust in accommodation sharing.

H8: Perceived value positively affects platform trust.

Perceived value is the key driver of adoption intention (Dodds et al., 1991; Wang et al., 2019). Experimental evidence on consumer behavior, together with the psychology literature, suggests that perceived value is useful in predicting consumer behavior (Chen & Chang, 2018; Liang et al., 2018; Wang et al., 2019). Recent research has also confirmed the prominent effect of perceived value on tourists' behavioral intentions related to online travel (Lee et al., 2018; Lien et al., 2015; Ponte et al., 2015) and accommodation sharing (Chen & Chang, 2018; Lee, 2020; Liang et al., 2018). The present study proposes the following hypothesis:

H9: Perceived value positively affects adoption intention.

3.4 PLATFORM TRUST

Trust in platforms rather than providers or consumers is the fundamental reason why a user adopts a sharing service such as Uber or Airbnb (Mittendorf, 2017;

Mao et al., 2020). As consumers access the host's accommodation services through the online platform, platform trust becomes a strong determinant affecting consumers' booking and check-in (Wang & Jeong, 2018). In the context of technology adoption, trust refers to one's judgment or expectation of a given IT application's helpfulness, reliability, and dependability (Teo et al., 2008; McKnight et al., 2011). Platform trust in this study is defined as tourists' belief that the home-sharing platform will be handled in accordance with their expectations. As in all the third-party e-commerce platforms, platform trust is built on the website's brand and reputation system using photos, ratings, reviews, and other sharing mechanisms (Teubner et al., 2016). In addition to its image and quality, consumers' initial platform trust is also influenced by consumers' disposition and cognition, as in the above assumptions.

Existing research has already explored the impact of trust on adoption intention in e-commerce and tourism settings. The empirical research of Kim et al. (2008) suggested that consumers' trust in an e-commerce site is the strongest predictor of online purchase intention, followed by the site's perceived value (benefits and risks). Rouibah et al. (2016) showed that customer trust is an important driver of online payment adoption. Hajli et al.'s (2017) research indicated that the more consumers trust a platform, the more they engage in online purchasing from an e-vendor. For travelers, Ponte et al. (2015) verified that trust and perceived value are the determinants of intention to purchase travel online. Ert et al. (2016) suggested that visual-based trust influences consumer decision-making when using Airbnb.

The effect of trust on adoption intention has been statistically verified in the contexts of e-commerce (Kim et al., 2008) and online payment (Rouibah et al., 2016). Destination trust positively influences intention to travel through electronic word-of-mouth (eWOM) in medical tourism (Abubakar & Ilkan, 2016). Platform trust is a salient driver of intention to use a ride-sharing application like Uber (Boateng et al., 2019; Lee et al., 2018). Trust and perceived value are the determinants of intention to purchase travel online (Ponte et al., 2015). Airbnb studies also have validated the significant impact of trust on the adoption intention (Birinci et al., 2018; Ert et al., 2016; Kong et al., 2020; Mao et al., 2020). So, the following hypothesis is proposed:

H10: Platform trust positively affects adoption intention.

3.5 OTHER CONSTRUCTS

As the dependent variable, adoption intention is the likelihood for the potential travelers to choose lodging through accommodation sharing platforms (Chen & Chang, 2018; Mao & Lyu, 2017), which is a vital predictor of behavior and has been empirically examined in the hospitality and tourism industry (Lien et al., 2015; Sparks & Browning, 2011). The author accepts the theoretical argument and empirical evidence that general personal innovativeness, self-efficacy, perceived value, and platform trust lead to adoption intention to lodge accommodation through sharing platforms.

As the extended SVM (ESVM) model, the human-product-adoption model (HPAM) is developed with five constructs and ten hypotheses. Specifically, general personal innovativeness and self-efficacy belong to human-related constructs; perceived value and platform trust are product-related variables; adoption intention is the adoption-related predictor. The detailed relationship hypotheses are shown in Figure 3.1.

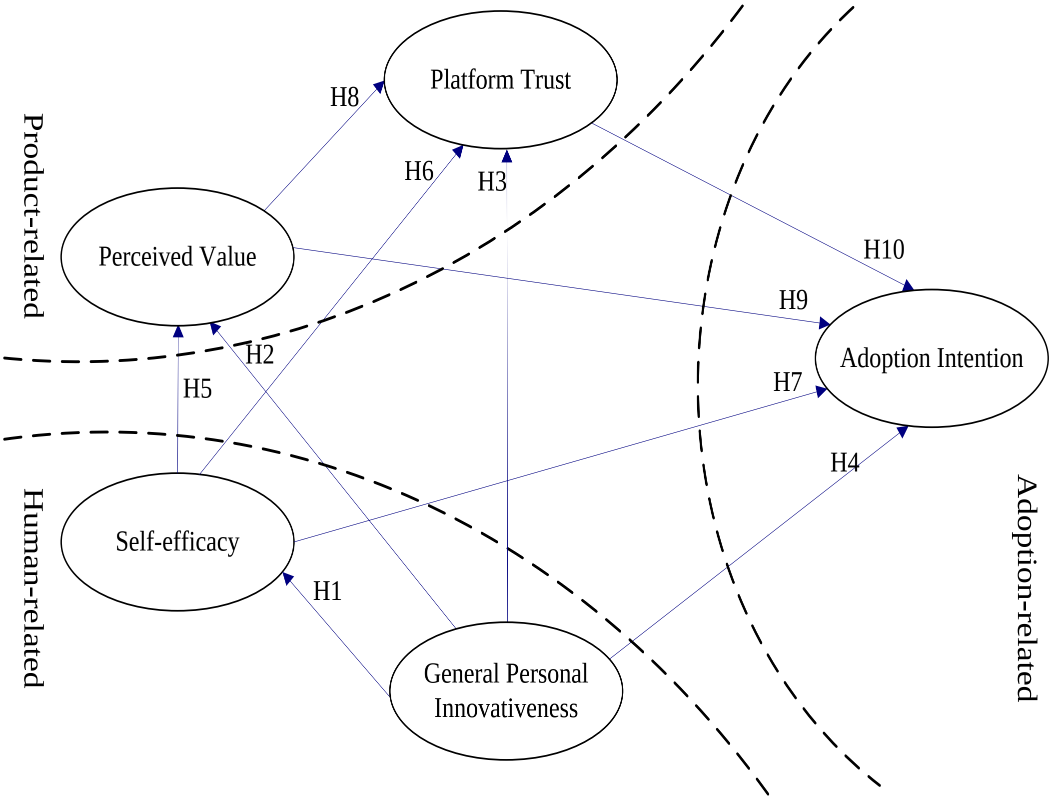

Figure 3.1 The constructs and hypotheses of the ESVM

Two additional constructs of perceived usefulness and perceived ease of use derived from Davis et al. (1989) are adopted to examine the classic TAM in the same context. PU and PEOU are also introduced to examine the classic TAM in the context compared with SVM. Many researchers in the hospitality and tourism fields employed TAM as the basic theoretical framework to build extended or combined models (Agag & EI-Masry, 2016; Amaro & Duarte, 2015; Ponte et al., 2015; Wang & Jeong, 2018). Pengnate and Sarathy (2017) demonstrated that the PU and PEOU are significant predictors of adoption intention to use rental websites. Therefore, we hypothesize that PU and PEOU are two antecedents of adoption intention to use accommodation sharing platforms. As a benchmark, TAM's performance will be compared with the identical parsimonious SVM (composed of H5, H7, and H9) and the extended SVM in the following empirical investigation.

CHAPTER 4
METHODOLOGY

To empirically test the developed model ESVM and compare the performance of SVM to TAM, a survey was conducted in China. Referring to the existing measure scales, a questionnaire was designed and collected by a professional survey firm Ipsos. The research methods are illustrated in this section.

4.1 INSTRUMENT DEVELOPMENT

To ensure the reliability and validity of our measures, all items were adapted from the literature and modified slightly to suit the context of this study (see Appendix A). The questionnaire was checked by two consumer behavior professors and then translated into Chinese and back to English. Three bilingual scholars examined the versions' consistency before conducting a pilot test at a university in China. Items were revised according to the pilot test. For example, considering the construct's consistency of general personal innovativeness, the item "I feel that I am an innovative person" was deleted because of its lower factor loading. Items about trust in hosts were excluded from platform trust. All measurement items were scored on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

4.2 SAMPLING METHOD AND DATA COLLECTION

A survey was performed by the Ipsos survey company in three Chinese metropolises: Beijing, Shanghai, and Guangzhou, which are respectively the most typical cities located in north China, east China and south China. Table 4.1 presents the sampling results with 329 valid data.

Table 4.1 A representative sample profiles

Characteristics	Items	Frequency	Percentage (%)
Gender	Male	168	51.1
	Female	161	48.9
Age	16-24	73	22.2
	25-34	83	25.2
	35-44	68	20.7
	45-54	62	18.8
	55-64	43	13.1
Residence	Beijing	111	33.7
	Shanghai	109	33.1
	Guangzhou	109	33.1
Occupation	Student	25	7.6
	Company employee	213	64.7
	Institutional staff	30	9.1
	Freelancer	43	13.1
	Others	18	5.5
Monthly Income (RMB)	0-2999	32	9.7
	3000-5999	113	34.3
	6000-8999	100	30.4
	9000-11999	49	14.9
	12000-	35	10.6
Familiarity	Never heard before	119	36.2
	Had heard before	210	63.8
Total		329	100.0

To ensure certain groups are represented and to reduce sampling variability, the stratified random sampling method was employed by gender, age and city that separated into a 2×5×3 strata sampling frame. The expected portions of 30 strata were calculated according to the most recent China sixth census data. The survey targeted 330 potential customers between 16 and 65 years old who had never lodged using home-sharing. The respondents who completed the questionnaire received a monetary coupon as a reward.

To determine if the sampling results were consistent with the census, the chi-square test was conducted by SPSS' Crosstabs, and the results indicated that gender, age, and city of the sample were represented for the p-values of their Pearson Chi-square far greater than the significance level of 0.05. Therefore, the sampling method and sample testing ensured the sample was representative of three major cities' population in China. Harman's single-factor test was employed to evaluate the common method bias. When an explanatory factor analysis of all items was conducted, the total variance for a single factor explained was 40.12%, which was less than 50% (Podsakoff et al., 2003). This result suggested that common method variance was unlikely in these data.

4.3 DATA ANALYSIS METHODS

Structural equation modeling (SEM) is a multivariate analytical approach used to simultaneously test and estimate complex causal relationships among variables (Ali & Kim, 2015; Williams et al., 2009). Partial Least Squares SEM (PLS-SEM) and covariance-based SEM (CB-SEM) are two different statistical methods to explore the latent variables' hypothetical relationships. To explain the latent constructs' variance through minimizing the error terms and maximizing the explanatory power of the endogenous constructs, PLS-SEM adopts a regression-based ordinary least squares estimation method (Hair et al., 2016). Employing a maximum likelihood estimation method, CB-SEM reproduces the covariance matrix by minimizing the difference between the observed and estimated covariance matrix, without focusing on explained variance (Hair et al., 2011; Ali & Kim, 2015).

In this study, PLS-SEM is utilized to test the hypotheses of the developed model, while CB-SEM is adopted to compare the models' performance. According to Hair et al. (2011), PLS-SEM is a proper method if the research objective is prediction and theory development, while CB-SEM is the appropriate method if the research objective is theory testing and confirmation. Given the suggestions, SmartPLS3.0, the PLS-SEM analysis tool, was employed to test and predict the developed model ESVM. As one of the CB-SEM analysis tools, the package of LAVAAN in R software was used to compare the TAM and SVM models.

CHAPTER 5
RESULTS AND DISCUSSION

The measurement model and structural model of the ESVM were tested by the PLS-SEM tool SmartPLS3.0. Specifically, the reliability and validity of the measurement scales were examined and reported. The proposed hypotheses were tested successfully, and the empirical results were reported. Through the CB-SEM method, the models' fit indices of SVM and TAM were acquired, and the comparative results were discussed in this section.

5.1 MEASUREMENT MODEL

The measured variables' reliability, internal consistency, convergence validity, and discriminant validity were evaluated by examining the measurement model via SmartPLS3.0. In bootstrapping, subsamples are created with observations randomly drawn (with replacement) from the original data set. To ensure the results' stability, we conducted 5,000 bootstrap subsamples (Hair et al., 2016).

Table 5.1 provides the test results of the measurement of constructs and items. The latent variables' reliability was evaluated by their composition reliability (CR) and Cronbach's alpha (CA). As shown in Table 5.1, CR and CA for each latent variable are above the critical value of 0.7, indicating that latent variables have good internal consistency. The average variance extracted (AVE) was used to assess the convergence validity. As shown in Table 5.1, the AVE of each latent variable in this study is greater than 0.5, indicating that the measurement scales have the acceptable convergence validity.

Table 5.1 Results of measurement

Construct	Items	Mean	STD	Factor loading	T-statistics	CA	CR	AVE
GPI	GPI1	5.34	1.10	0.92	84.33	0.90	0.94	0.84
	GPI2	5.17	1.15	0.91	81.16			
	GPI3	5.23	1.16	0.92	90.11			
SE	SE1	5.32	0.92	0.88	55.41	0.85	0.91	0.77
	SE2	5.30	0.95	0.91	79.17			
	SE3	4.99	0.98	0.83	35.52			
PV	PV1	4.78	0.95	0.84	33.76	0.88	0.92	0.73
	PV2	4.69	0.99	0.84	40.75			
	PV3	4.97	0.90	0.86	44.19			
	PV4	4.91	0.93	0.88	65.00			
TR	TR1	4.88	0.94	0.88	53.34	0.87	0.92	0.79
	TR2	4.94	0.97	0.90	64.28			
	TR3	4.75	1.08	0.89	67.14			
IN	IN1	5.12	1.02	0.94	90.47	0.92	0.95	0.86
	IN2	5.20	1.00	0.92	74.09			
	IN3	5.17	0.99	0.92	54.58			
PU	PU1	4.87	1.02	0.76	25.34	0.88	0.91	0.76
	PU2	4.68	0.99	0.72	21.22			
	PU3	5.04	1.00	0.84	50.67			
	PU4	5.26	0.99	0.80	36.90			
	PU5	5.21	0.93	0.81	37.72			
	PU6	5.31	0.96	0.78	36.85			
PEOU	PEOU1	5.28	1.00	0.83	35.10	0.83	0.89	0.66
	PEOU2	5.15	0.91	0.82	31.52			
	PEOU3	5.37	0.96	0.78	18.91			
	PEOU4	5.31	0.92	0.83	32.62			

According to the results of constructs' cross-loadings (see Table 5.2), the cross-loadings also indicate the support of constructs' convergence validity and discriminate validity. The factor loadings of each construct are significant and greater than the recommended value of 0.7. According to Table 5.2, no item cross-loaded higher on another construct than on its own construct, demonstrating the discriminant validity (Hair et al., 2011).

Table 5.2 Construct cross loadings

	GPI	IN	PEOU	PU	PV	SE	TR
GPI1	**0.92**	0.64	0.38	0.45	0.54	0.66	0.59
GPI 2	**0.91**	0.61	0.39	0.40	0.54	0.68	0.59
GPI 3	**0.92**	0.61	0.38	0.42	0.56	0.67	0.57
IN1	0.62	**0.94**	0.46	0.54	0.67	0.72	0.70
IN2	0.63	**0.92**	0.45	0.48	0.62	0.70	0.66
IN3	0.62	**0.92**	0.46	0.50	0.64	0.67	0.68
PEOU1	0.34	0.42	**0.83**	0.50	0.42	0.49	0.39
PEOU2	0.33	0.46	**0.82**	0.60	0.46	0.46	0.48
PEOU3	0.25	0.31	**0.78**	0.44	0.34	0.36	0.27
PEOU4	0.41	0.40	**0.83**	0.57	0.47	0.47	0.45
PU1	0.32	0.35	0.52	**0.76**	0.46	0.34	0.45
PU2	0.37	0.41	0.43	**0.72**	0.39	0.38	0.44
PU3	0.38	0.45	0.51	**0.84**	0.49	0.42	0.49
PU4	0.30	0.38	0.52	**0.80**	0.41	0.38	0.43
PU5	0.34	0.41	0.52	**0.81**	0.45	0.41	0.46
PU6	0.47	0.54	0.58	**0.78**	0.52	0.50	0.51
PV1	0.43	0.51	0.41	0.44	**0.84**	0.53	0.59
PV2	0.50	0.60	0.43	0.51	**0.84**	0.57	0.68
PV3	0.55	0.62	0.47	0.50	**0.86**	0.59	0.59
PV4	0.54	0.64	0.47	0.53	**0.88**	0.61	0.67
SE1	0.66	0.67	0.53	0.47	0.60	**0.88**	0.61
SE2	0.64	0.71	0.51	0.46	0.60	**0.91**	0.65
SE3	0.62	0.59	0.40	0.43	0.57	**0.83**	0.67
TR1	0.60	0.69	0.45	0.54	0.66	0.70	**0.88**
TR2	0.57	0.63	0.42	0.46	0.63	0.65	**0.90**
TR3	0.54	0.64	0.46	0.58	0.69	0.62	**0.89**

All diagonal elements of the square root of AVE shown in table 5.3 are greater than the inter-construct correlations, which means adequate discriminant validity (Henseler et al., 2015). As a reliable alternative approach to assessing discriminant validity, all values of HTMT (Heterotrait–Monotrait ratio) are significantly below the threshold of 0.90 suggested by Benitez et al. (2020). Considering the above evaluation results comprehensively, the discriminant validity of latent variables is supported.

Table 5.3 The correlation matrix of latent variables with AVE and HTMT

Constructs	GPI	IN	PEOU	PU	PV	SE	TR
GPI	**0.92**	*0.74*	*0.47*	*0.52*	*0.66*	*0.84*	*0.72*
IN	0.68	**0.93**	*0.56*	*0.60*	*0.77*	*0.85*	*0.82*
PEOU	0.42	0.49	**0.81**	*0.76*	*0.60*	*0.65*	*0.57*
PU	0.47	0.55	0.66	**0.79**	*0.66*	*0.60*	*0.68*
PV	0.60	0.70	0.52	0.58	**0.86**	*0.78*	*0.84*
SE	0.73	0.75	0.55	0.52	0.67	**0.88**	*0.85*
TR	0.64	0.73	0.50	0.59	0.74	0.74	**0.89**

Note: The lower left diagonal is the correlation matrix of latent variables; the bold diagonal element is square root of AVE; the upper right diagonal in italics is HTMT.

5.2 HYPOTHESES TEST OF THE ESVM MODEL

By PLS-SEM analysis, the result of the hypotheses test of ESVM is shown in Figure 5.1, which shows that all the paths among variables are significant as expected. Specifically, GPI significantly predicted SE (H1 supported: β = .73, t = 22.71, p < .001), PV (H2 supported: β = .22, t = 3.96, p < .001), PT (H3 supported: β = .12, t = 2.29, p< .05), and IN (H4 supported: β = .18, t = 3.01, p < .01). SE significantly led to PV (H5 supported: β = .51, t = 9.13, p < .001), PT (H6 supported: β = .37, t = 5.9, p < .001), and IN (H7 supported: β = .30, t = 4.17, p < .001). In addition, PV was found to predict PT (H8 supported: β = .43, t = 8.92, p < .001) and IN (H9 supported: β = .20, t = 4.12, p < .001). PT significantly predicted IN (H10 supported: β = .25, t = 3.89, p < .001).

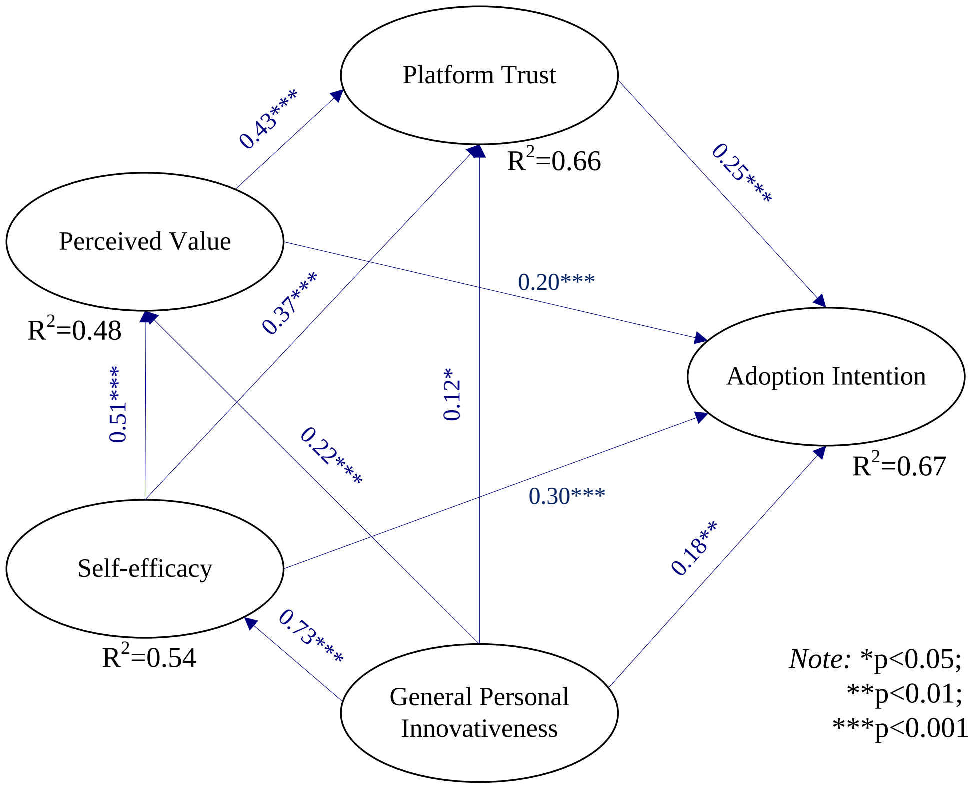

Figure 5.1 The PLS-SEM result of ESVM

The inner model was also evaluated using the R^2 value as recommended by Hair et al. (2016). Figure 5.1 shows that the R^2 values for all endogenous variables exceeded the substantial value of 0.26 (Cohen, 1988), demonstrating the proposed model's reliable predictive power. To assess the PLS-PM structural model, the effect size f^2 was evaluated to examine the predictive variable effects in the structural model with values of about 0.02, 0.15 or 0.35 indicating that the exogenous latent variable has a small, medium or large effect on the endogenous latent variable, respectively (Chin, 1998; Hair et al., 2016). Results indicated that GPI ($f^2 = 0.04$), PV ($f^2 = 0.05$), SE ($f^2 = 0.09$), and PT ($f^2 = 0.07$) each had a medium-level explanatory effect ($0.02 < f^2 < 0.15$) on adoption intention.

5.3 COMPARATIVE STUDY OF SVM AND TAM

By PLS-SEM analysis, the result of SVM and TAM's hypotheses tests are shown in Figure 5.2, which shows that all the path coefficients are significant.

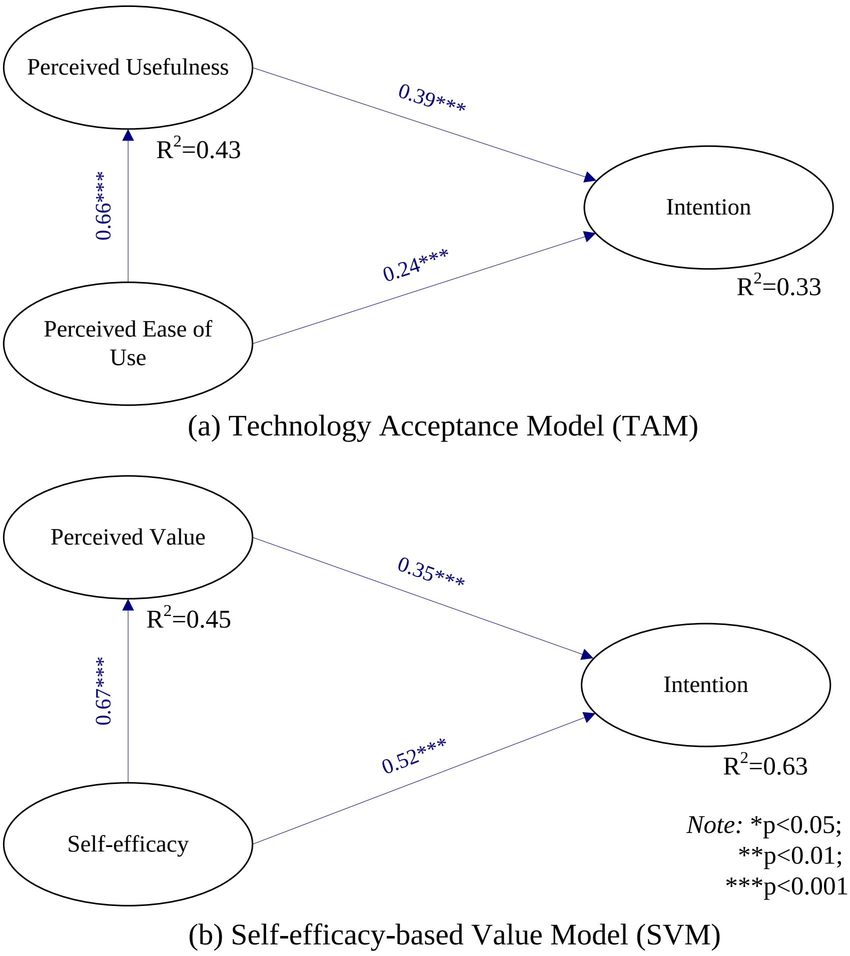

Figure 5.2 The PLS-SEM results of TAM and SVM

PU (β= .39, p < .001) and PEOU (β= .24, p < .001) are the significant predictors of intention of lodging through Airbnb in TAM. PEOU significantly influences PU of Airbnb with a path coefficient of (β= .66, p < .001). Similarly, PV (β= .35, p < .001) and SE (β= .52, p < .001) are also the significant predictors of intention of lodging through Airbnb in SVM. SE of using Airbnb significantly influences PV with a path coefficient of (β= .67, p < .001). By examining the PLS-SEM results of TAM and SVM, models are all acceptable. However, SVM is overwhelmingly better in explanatory power (R^2=0.63) than TAM (R^2=0.33) within an identical parsimonious model structure and same application scenario.

Furthermore, structural equation modeling analyses between TAM and SVM were conducted by CB-SEM to comprehensively compare the different models' performance. This study employed R software with the package of LAVAAN (Latent Variable Analysis). Overall, the results demonstrate that the models' fit indices (like Chi-S/df, RMSEA, NFI, NNFI, CFI, IFI, GFI, SRMR) are all acceptable (see Table 5.4). However, according to some recommendations for evaluating structural equation models' fit (Schreiber, 2017; Schermelleh-Engel et al., 2003), the fit indices of SVM are overwhelmingly better than TAM's, especially the indices of information criteria. AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are usually adopted to compare alternative models and determine which model explains the given data better (Schreiber, 2017). The smaller the AIC and BIC values, the better the model serves as an approximation to "reality" (Hong et al., 2006). The result of Table 5.4 shows that all information criterion indices favor SVM over TAM.

Table 5.4 Summary and comparison of fit indices for the structure equation modeling

Fit indices	Acceptable	TAM	SVM	ESVM
Chi-S/df	<3	2.346	**1.564**	1.955
RMSEA	<0.08	0.064	**0.041**	0.055
SRMR	<0.08	0.044	**0.025**	0.031
NFI	>0.90	0.942	**0.979**	0.956
NNFI (TLI)	>0.90	0.957	**0.989**	0.971
CFI	>0.90	0.966	**0.992**	0.978
IFI	>0.90	0.966	**0.992**	0.978
GFI	>0.90	0.936	**0.972**	0.934
AIC	-	9616.478	**6765.438**	10880.656
BIC	-	9726.563	**6852.747**	11040.090

Note: Bold shows the best parameter in comparison; "-" means the smaller the better.

To reveal more information of the model development and assessment, Table 5.4 also listed all fit indices result of ESVM at the same time. Compared to SVM, the ESVM improved the explanatory power for intention with two more antecedents but sacrificed the performance of fit indices.

CHAPTER 6
CONCLUSIONS

In summary, some foundational results can be acquired from the empirical investigation: (1) TAM, SVM, and ESVM are qualified models to explain and predict the travelers' intention of lodging through Airbnb; (2) with identical structure and the same number of predictors, as a basic framework model, SVM is clearly superior to TAM; (3) the ESVM reveals more information of lodging through Airbnb with additional predictors.

6.1 THEORETICAL FINDINGS

Unlike previous studies on innovation adoption that emphasized product (or service)-centered factors, this study proposes a comprehensive theoretical model HPAM based on SVM to explain the relationship between user, product, and intention. The model clarifies why tourists adopt home-sharing and explains the formations of self-efficacy, perceived value, platform trust, and intention. It verifies that self-efficacy and perceived value are major factors that commonly affect the degree of trust. The finding demonstrates that personal factors, including general personal innovativeness and self-efficacy, are vital determinants influencing product perception (such as perceived value and platform trust) and behavior intention. Self-efficacy and platform trust are the most important reasons why tourists use Airbnb. Secondly, perceived value and personal innovativeness influence tourists to adopt Airbnb. As a comprehensive model, the extended SVM model HPAM explains why guests choose to use Airbnb.

A comparative analysis of TAM and SVM was conducted, and the results indicate that SVM is superior to TAM in all model fitness indices with the identical model structure. Given the same parsimony, therefore, SVM is significantly more explanatory power than the classic technology adoption model. The reason could be the inherent logic and comprehensiveness of SVM derived from the reciprocal determinism of SCT. Specifically, self-efficacy is an excellent personal determinant that reflects self-confidence to use a specific innovation, influence product awareness, and predict behavior. By contrast, PEOU is a non-typical personal determinant, which integrates product-related attributes with individual learning ability. According to the meta-analysis by Lee et al. (2003) and Sun & Zhang (2006), PEOU does not predict the intention accurately, although PEOU has been proved as a stable antecedent of PU. Compared to perceived value (PV), perceived usefulness (PU) can be seen as a part of PV because PV includes functional benefits and non-functional benefits, while PU is similar to functional benefits. As an overall perception of a product's benefits over sacrifices, perceived value serves better to predict intention, especially considering costs or risks in the individual consumer context. Comparatively, PU is one part of perceived value as functional benefits. According to the consumer value theory by Sweeney & Soutar (2001), positive perceived value embraces the functional, emotional social value and others. Based on the above theoretical analysis, it is easy to understand why the empirical performance of SVM is better than TAM to explain tourists' intention with the identical model structure.

6.2 PRACTICAL IMPLICATIONS

According to Annual Report on China's Sharing Economy Development (2020) and China Internet Network Information Center (2020), as an emerging and developing Chinese market, Airbnb guests have increased by 580% in the past five years, however, most of the population (more than 90% of netizens) in China have never used accommodation sharing platforms. In agreement with Ert et al. (2016), home-sharing service is still far from reaching its full potential. Based on this empirical study, the potential users in major Chinese cities have a higher intention of using the home-sharing platform (with the IN's total mean of 5.16), which reveals a potentially enormous demand. The sharing platforms including Airbnb and local startups should and could attract more users to experience home-sharing services. This study will suggest ways to expand the accommodation sharing market, especially in major Chinese cities.

Because general personal innovativeness (GPI) and special self-efficacy (SE) influence how much value can be perceived and transformed into actual purchase behavior, it is meaningful to identify the different user groups by typical indicators of GPI and SE. It is technologically feasible for enterprisers to determine the underlying psychological variables with accessible indicators such as age, education, occupation, and other characteristics or consumption records via database inquiry or big data analysis. It is economical and efficient to initially deliver advertisements to people with higher SE and GPI. Previous studies also showed that even if service suppliers provide evidence of good value, users might regard it as neither necessary nor beneficial because of what kind of users they are (Kwon et al., 2007). Therefore, precision marketing built on a big data analysis is an efficient strategy for managers. The operators of home-sharing platforms could identify the early adopters through association analysis and cluster analysis based on user experience in other innovative services such as Uber and online travel agents. Fortunately, the total mean of GPI (5.25) and SE (5.20) indicate potential users in major Chinese cities are ready to accept innovation and believe they can use Airbnb to a certain extent.

Second, the potential users have perceived the value of the home-sharing, and they trust the platform of Airbnb. Compared to the costs, such as various risks, efforts, and financial costs, the respondents believe the benefits of home-sharing (including but not limited to PU and PEOU with a total mean of 5.06 and 5.28, respectively) are positive for them (referring to the PV's total mean of 4.84 and PT's total mean of 4.85 in this study). System developers should design and update the platform to be more friendly, convenient, effective and safe. As perceived value increases, the trust in the platform also increases, and tourists are more likely to use Airbnb. Both sharing platforms and hosts should create more positive value for guests. Specifically, they can lower the threshold of service access, reduce perceived risk, enhance existing customer experience, trigger positive word-of-mouth (WOM) and online review, and maintain a competitive advantage over other accommodation options. The service managers and hosts should conduct some online or offline service remediation to reduce guests' negative perceived value. To acquire the guest's trust, specific marketing strategies and guidance should be developed for different user segmentation based on personality indicators. To improve home-sharing platform trust, Airbnb, as a foreign company, should upgrade user-friendly sites, improve the credit evaluation system, and promote the self-branding image referring to local Chinese culture and tourists' preference.

6.3 LIMITATION AND FUTURE RESEARCH

Despite meaningful findings, limitations remain, and more research should be done. (1) The sample was restricted to major Chinese metropolises, which could influence the generalization of the results. (2) This comparative study between SVM and TAM focused exclusively on Airbnb. To demonstrate the generality of this conclusion, more comparative studies in different fields should be conducted. (3) To apply to practical management, users' personal indicators such as self-efficacy and innovativeness should be established according to the existing indicators and demographic information in the database or developed by designing new measurement scales. (4) As the users of home-sharing platforms, guests and hosts are the two sides of a coin. The model could expand to hosts’ contexts and compare to different user groups. (5) The possible antecedents of intention, such as social media, environmental awareness and privacy, could be considered and compared with their influence in different cultures and countries.

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APPENDIX A

QUESTIONNAIRE

Table A.1 Survey questionnaire measurement and sources

Construct	Label	Item	Source
General Personal Innovativeness	GPI1	I like to experiment with something new.	Goldsmith (2002)
	GPI2	I am generally willing to try out new things.	
	GPI3	I usually tend to adopt innovation earlier than my peers.	
Self-efficacy	SE1	I believe I am able to use Airbnb to rent in if I want.	Zhu et al. (2010; 2017)
	SE2	I believe I can master the skills of lodging through Airbnb.	
	SE3	I believe I can deal with problems encountered during using Airbnb.	
Perceived Value	PV1	Compared to the fee I need to pay, home-sharing accommodation mode will offer more value for the money.	Kim et al. (2007)
	PV2	Compared to the potential risk, lodging accommodation mode will be worthwhile to me.	
	PV3	Compared to the possible loss, lodging through Airbnb will be beneficial to me.	
	PV4	Overall, lodging through Airbnb will deliver me good value.	
Platform Trust	PT1	I think Airbnb's system is trustworthy.	Pengnate & Sarathy, (2017)
	PT2	I believe Airbnb is one that keeps promises and commitments.	
	PT3	I trust that Airbnb will keep my best interests in mind.	
Perceived Usefulness		Lodging through Airbnb will…	Davis, (1989); Venkatesh
	PU1	…enable me to accomplish tasks more quickly.	
	PU2	…improve my rental performance.	
	PU3	…enhance my rental effectiveness.	

	PU4	…save me time and effort.	& Davis
	PU5	…make it easier to rent.	(2000)
	PU6	Overall, it will be useful to rent in.	
Perceived	PEOU1	…be easy for me to learn to use.	
Ease of Use	PEOU2	…be easy to complete my rental task.	Davis
	PEOU3	…be clear and understandable.	(1989)
	PEOU4	Overall, I will find it easy to use.	
Intention	IN1	I predict I would lodge through Airbnb in the future.	
	IN2	I plan to use Airbnb to rent in a room or unit in the future.	Davis et al. (1989)
	IN3	I intend to rent in a room or unit through Airbnb in the future.	