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Research Article

The more we get together, the more we can save? A transaction cost perspective

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ABSTRACT

Although sharing is not a new subject, sharing behavior enabled by peer-to-peer software technologies is a recent phenomenon. Studies have explored the impact of the sharing economy on consumers by applying the theory of planned behavior, complexity theory, and social exchange theory, but few studies have explored transaction costs in the sharing economy. By integrating network externalities with transaction cost theory, this study explores transaction costs and their determinants in the context of the sharing economy. Structural equation modeling analysis was conducted on data from 375 users of Airbnb. The findings indicate that personalization of asset specificity and transaction frequency negatively influence transaction costs. Additionally, learning of asset specificity and transaction uncertainty positively affects transaction costs, which in turn influence behavioral intention. Furthermore, perceived complementarity has a direct effect on transaction uncertainty. Finally, the number of users moderates the relationship between transaction costs and behavioral intention. This understanding will assist managers in numerous industries impacted by the rapid development of the sharing economy by providing them with strategies for coping with this trend.

1. Introduction

The sharing economy is a socioeconomic system mediated by a digital platform that enables individuals or organizations to exchange goods or services (Xu, 2020). It is characterized by nonownership, temporary access, and the redistribution of material goods (Kathan, Matzler, & Veider, 2016). This new sharing model has flourished across various industries and has been utilized to provide transportation (e.g., Uber, DiDi), accommodation (e.g., Airbnb), tourism (e.g., Vayable, Tripforeal), restaurant (e.g., Kitchit, Eatwith), and local delivery (e.g., Instacart, Postmates) services. The commercial sharing industry is increasingly popular, with approximately 9000 start-ups appearing worldwide between 2014 and 2019 (PricewaterhouseCoopers, 2015). Some businesses in the sharing economy are rapidly scaling up (Böcker & Meelen, 2017). Two of the most dominant platforms in the sharing economy, Uber and Airbnb, were valued at $70 billion 7 (Bloomberg, 2020) and $31 billion (Airbnb, 2020), respectively, in 2019. Other sharing economy platforms are valued at more than $1 billion (Insights, 2018). The global market value of services offered through the sharing economy is expected to increase from $15 billion in 2014 to $335 billion by 2025 (Statista, 2020).

Transactions constitute the core economic activity in the sharing economy (Mair & Reischauer, 2017). A sharing platform monetizes the interaction between the supply and demand sides in a two-sided market (Akbar & Tracogna, 2018). Suppliers and consumers transact via a commercial sharing platform, which facilitates a nonownership transfer through which consumers obtain temporary access to consumption goods. According to classical economic theory, the transaction cost is zero when all economic agents are well informed (Williamson, 1985). Transaction costs are defined as costs related to an economic exchange between agents (Robins, 1987). In the real world, economic agents possess limited information concerning the quality or price of products, and thus transaction costs exist in markets (Coase, 1937). Commercial sharing is no exception. However, few studies have explored the transaction costs of the sharing economy, with the exceptions of Akbar and Tracogna (2018) and Henten and Windekilde (2016). Akbar and Tracogna (2018) posited three hypotheses to understand how transaction features influence the emergence of sharing platforms, and Henten and Windekilde (2016) applied transaction cost theory (TCT) to explain how the sharing economy has changed the structure of industries. Customers

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prefer to shop using a channel with relatively low transaction costs (Teo & Yu, 2005), and hence transaction costs influence the use of commercial sharing platforms (Sutherland & Jarrahi, 2018). Given the costs of participating in the sharing economy, the role of transaction costs warrants further study.

Initially developed by Coase (1937) and extended by Williamson (1975), TCT explains the relationship between the characteristics of exchange and the relevant governance structure. According to TCT, organizations and individuals choose the most appropriate governance structure or strategies to minimize their transaction costs. Williamson (1985) posited that environmental uncertainty, a small number of trades, and asset specificity increase transaction costs. Furthermore, TCT can be applied to clarify a transaction subject's choice of some given trading partner (Che, Peng, Lim, & Hua, 2015; Qi, Chan, Hu, & Li, 2020). This study adopted TCT to explore the transaction costs borne on sharing economy platforms because, according to this theory, intermediaries, such as brokers and digital platforms, make markets more efficient by reducing transaction costs (Schenk, Guittard, & Pénin, 2019). Digital platforms bridge suppliers and consumers, which was previously only possible to a limited extent. Whether a service demander chooses to transact via a digital platform is determined by the perceived transaction costs. Because consumers on sharing economy platforms are seeking to transact in a manner that minimizes transaction costs, TCT is a viable framework for explaining consumer decisions regarding platform selection.

By integrating network externalities with TCT, this study explores transaction costs and their determinants in the context of the sharing economy. The research aims of this study were as follows: (1) to explore transaction costs in the context of the sharing economy, (2) to investigate the antecedents of transaction costs, specifically in terms of asset specificity, uncertainty, and transaction frequency, and their influences on transaction costs in the context of the sharing economy, and (3) to elucidate the impacts of network externalities on consumers' behavioral intention. The findings can help managers better cope with the increasing popularity and sophistication of the sharing economy.

The remaining parts of this study are structured as follows. Section 2 presents the literature review. Section 3 provides the theoretical background and states the hypotheses. Section 4 describes the methodology, including the data collection procedure and the demographic profile of the respondents. Section 5 details the analysis results. Section 6 discusses the research findings, theoretical implications, managerial implications, research limitations, and directions for future research. Finally, Section 7 concludes this study.

2. Literature review

2.1. Research on airbnb

A sharing economy is defined as a system of "consumers granting each other temporary access to their underutilized physical assets, possibly for money" (Böcker & Meelen, 2017, p. 29). The rise of the sharing economy is associated with digital platforms where firms create two-sided markets to earn a profit (Dreyer, Lüdeke-Freund, Hamann, & Faccer, 2017). Digital platforms enable interaction between sharing parties, but neither owns the underutilized resources available for transactions or hires service providers (i.e., hosts) (Lee, Yang, & Koo, 2019). For example, Uber is a digital platform that offers transportation services to consumers by utilizing the untapped resource that is ordinary car owners. Car owners benefit by earning money by providing transportation services, and consumers benefit by being able to travel long or short distances at rates cheaper than those of a taxi. Digital platforms form networks that have transformed traditional consumption models (e.g., business-to-consumer transactions) into innovative consumption models (peer-to peer transactions) by connecting suppliers and consumers (Lang et al., 2020; Lee et al., 2019).

Airbnb, the pioneer in the home-sharing market, is the most well-known and dominant sharing economy platform (Bae, Lee, Suh, & Suh, 2017; Vith, Oberg, Höllerer, & Meyer, 2019). Established in 2008, Airbnb has hosted 60 million guests and offers over 5 million listings in more than 81,000 cities and 191 countries (Airbnb, 2020). The company has been growing exponentially, and its valuation stood at $31 billion in the middle of 2017 (Thomas, 2017). Airbnb is a digital platform through which hosts can share their spare rooms, providing them to guests who seek short-term accommodation. Moreover, Airbnb possesses three key characteristics of a sharing economy (Richardson, 2015). First, it is a digital platform that reduces the costs of connecting many potential hosts and guests. Second, it provides peer-to-peer interactions, and the roles of guests and hosts are theoretically interchangeable. Third, it provides access-based transactions in which guests gain access to, rather than possession of, a hospitable space for a short time. This study adopted Airbnb as its research context to explore consumers' intention to use a sharing economy platform.

Appendix 1 lists studies that have focused on Airbnb. Some studies have qualitatively explored the business model of the sharing economy through case analyses (e.g., Henten & Windekilde, 2016; Mercier-Roy & Mailhot, 2019) or interviews (e.g., Thaichon, Surachartkumtonkun, Singhal, & Alabastro, 2020). Other studies have quantitatively investigated consumer behaviors or evaluations by applying data-mining procedures to the content of the Airbnb website (e.g., Xu & Schrier, 2019; Zhang, 2019) or examined consumer motivation (e.g., Tamilmani, Rana, Nunkoo, Raghavan, & Dwivedi, 2020), trust (e.g., Nadeem, Juntunen, Shirazi, & Hajli, 2020; Nisar, Hajli, Prabhakar, & Dwivedi, 2020), perceptions of value (e.g., Chen & Chang, 2018; Clauss, Harengel, & Hock, 2019), quality (e.g., Huarng & Yu, 2019; Marimon, Llach, Alonso-Almeida, & Mas-Machuca, 2019; Zhao & Rahman, 2019), risk (e.g., Jun, 2020; Yi, Yuan, & Yoo, 2020), satisfaction (e.g., Möhlmann, 2015a; Sutherland & Kiatkawsin, 2020), privacy concerns (e.g., Nisar et al., 2020), and continuance intention (e.g., Califf, Brooks, & Longstreet, 2020) through questionnaire surveys.

2.2. Transaction cost theory

Coase (1937) recognized the prevalence of transaction costs and used the transaction cost approach to explain industrial structures. According to classical economic theory, transaction costs are absent when all economic agents have perfect information (Williamson, 1985). Transaction costs are defined as costs related to an economic exchange between agents (Robins, 1987). Extending Coase (1937) concept, Williamson (1981) proposed two principles of human behavior, namely, bounded rationality and opportunism. Bounded rationality describes how individuals attempt to behave rationally under the conditions of limited information and a limited capacity to process information, and opportunism describes how habitual human actions are driven by self-interest (Saleh, Ali, Quazi, & Wickramasekera, 2015). Because economic agents have limited information on the quality or price of products, real-world markets feature transaction costs (Hsieh, Huang, & Lee, 2016).

(Williamson, 1981) posited that three environmental factors (asset specificity, uncertainty, and transaction frequency) produce transaction costs, either ex ante or ex post. Asset specificity is defined as "a specialized investment that cannot be redeployed to alternative uses or by alternative users except at a loss of productive value" (Williamson, 1996, p. 377). Uncertainty refers to the "strategic nondisclosure, disguise, or distortion of information" (Williamson, 1985, p. 57). Transaction frequency refers to "buyer activity in the market" (Williamson, 1979, p. 247). In particular, transaction costs are determined by transaction features that include specific or nonspecific assets, can have high or low uncertainty, and can occur rarely or frequently (Teo & Yu, 2005). Williamson, (1981) further investigated the impact of governance structure on transaction features. Firms adopt alternative governance structures (i.e., markets, hierarchies, and hybrid forms) to balance production and transaction costs and minimize transaction costs

(Yuan, Chu, Lai, & Wu, 2020). Firms face high transactions costs when transactions are highly specific, uncertain, and frequent. If transaction costs outweigh production costs, firms can choose to adopt hierarchical governance rather than market-based governance, or they can cease to engage in transactions altogether (Chang, Gurbaxani, & Ravindran, 2017).

TCT has been extended from the firm or organizational level to the individual level. For example, Che et al. (2015) proposed that three context-specific TCT factors, unpredictability, trust, and personalization specificity, directly affect the consumer's intention to revisit a website. Yen, Hsu, and Chang (2013) determined that repurchase intention in online auctions is determined by TCT factors, chiefly uncertainty and frequency. At the individual level, TCT explains why an individual chooses a particular transaction partner or channel instead of another. Buyers prefer to transact with the seller with the lowest transaction costs (Liang & Huang, 1998; Tang, Chen, Hua, & Fu, 2020). Transactions, including those on digital sharing platforms, necessarily entail transaction costs (Mäntymäki, Baiyere, & Islam, 2019). In the commercial sharing market, transacting consumers bear costs, including those incurred from searching, contacting, and contracting (Henten & Windekilde, 2016). TCT provides a viable model for understanding the sharing economy (Henten & Windekilde, 2016). Accordingly, to obtain a comprehensive understanding of transaction costs based from the consumer's viewpoint, the present study adopted TCT as the theoretical foundation to explore transaction costs and their antecedents in the context of the sharing economy.

Transaction costs encompass all expected costs (Ahluwalia, Mahto, & Guerrero, 2020). For example, Aubert, Rivard, and Patry (1996) argued that transaction costs include those resulting from organizing information, monitoring transactions, coordinating the behaviors of participants, and safeguarding the interests of the transacting parties. Teo and Yu (2005) and Hsu and Lin (2020) adopted categorized searching, monitoring, and adaptation costs as three types of transaction costs. Bugshan, Nick Hajli, Lin, Featherman, and Cohen (2014) indicated that transaction costs can include information searching and other costs related to monitoring activities. According to Ye and Kankanhalli (2015), coordination, communication, negotiation, process monitoring, and performance evaluation are elements of transaction costs. Aswani, Kar, Ilavarasan, and Dwivedi (2018) indicated that search engine marketing services incur several transaction costs, including agency problems, coordination costs, loss of noncontractible value, and cost of fit. Rangaswamy et al. (2020) posited that a digital business platform reduces ex post transaction costs, namely, search and decision costs, as well as production (cocreation) costs. Ma et al. (2020) argued that the transaction costs on a public car-sharing platform related to the cost of picking up the car. Sarin, Kar, and Ilavarasan (2021) suggested that search cost, agency cost, and loss of non-contractible value are the components of transaction cost economics. Qi et al. (2020) argued that a foreign firm deploying cross-border E-commerce as an entry mode faces high transaction costs related to searching, negotiation, and enforcement.

Because transaction costs in the online purchasing context correspond to the transaction costs of using digital platforms in the sharing economy, this paper defines transaction costs as those involved in transaction-related activities, following Teo and Yu (2005). Searching, monitoring, and adaptation costs were identified as the three types of transaction costs in the context of the sharing economy. This study adopted the definition of Teo and Yu (2005): searching costs are the time and effort expended in searching for information and comparing products, and monitoring costs are those expended in ensuring that the terms of the transaction contract can be met. Adaptation costs are defined as the time and effort required for changes of services and the relevant support during the period of the transaction contract.

3. Theoretical background and hypotheses development

3.1. Antecedents of transaction costs

The explanatory power of TCT stems from three antecedents that characterize transaction costs—asset specificity, uncertainty, and transaction frequency (Williamson, 1981)—and they are adopted in this study. Asset specificity refers to physical or intangible assets that individuals use in support of particular transactions (Buvik & Andersen, 2002; Wu, Chen, Chen, & Cheng, 2014). When transactions require specific assets, switching to alternatives is difficult, and people tend to depend heavily on the transacting parties (Kim, 2017). A high degree of asset specificity deters transacting parties from switching (Jones & Leonard, 2007).

Uncertainty refers to the costs related to unexpected outcomes and information asymmetries during the transaction process (Liang & Huang, 1998). Uncertainty underscores human inability to predict events or contingencies (Che et al., 2015; Teo & Yu, 2005). Although a digital platform attracts consumers because it is inexpensive and convenient, consumers may also experience uncertainty when using a technology-intensive platform. Transactions with relatively high uncertainty involve a higher transaction cost, which may cause the transaction to fail. When a transaction is high in uncertainty, consumers have difficulty identifying future contingencies and may hesitate to commit to the seller (Saleh et al., 2015). In the context of the sharing economy, uncertainty reflects the difficulty in predicting which issues are relevant in a particular transaction.

Transaction frequency is an antecedent of transaction costs that refers to the repetition of similar transactions (Chen, Su, & Hiele, 2017; Miranda & Kim, 2006; Promsivapallop, Jones, & Roper, 2015). Devaraj, Fan, and Kohli (2006) and Hsieh et al. (2016) defined frequency as the pattern of recurrence of transactions over a period of time, whereas Klein, Frazier, and Roth (1990) defined it as a dichotomous construct where transactions are divided into one-time and recurring transactions. Frequent transactions tend to be controllable by the transaction partner (Saleh et al., 2015). In this study, transaction frequency is defined as the volume of recurrent transactions on a digital sharing platform.

3.1.1. Asset specificity

Studies have identified several asset specificity factors. Williamson (1981) indicated that an asset can have site specificity, physical asset specificity, and human asset specificity. Chiou (2010) stated that specific asset investment involves knowledge, human assets, physical assets, and company-specific routines. Wu, Chen, and Chen (2015) observed that business-to-business-related studies have mainly focused on the investment of physical and human assets when discussing specific assets. Che et al. (2015) suggested that personalization specificity and trust are specific assets that create a lock-in effect. Hsieh et al. (2016) proposed two types of specific assets: dedicated assets (specific equipment and machinery designed for a single purpose) and human assets (transaction-specific knowledge or human capital, achieved through specialized training or learning by doing).

Because consumers do not need to make any durable asset investment in the context of the sharing economy, asset specificity here refers to an individual's intangible investments, which cannot be removed for other purposes, when using a digital platform. Consumers seek individuals who possess underutilized resources through mobile applications or websites. Because those tangible assets—the mobile application or website—can be used for other purposes, they cannot be classified as specific assets. As consumers must spend time and effort to complete transactions, service-specific investment is necessary on a sharing platform. Service-specific investments refer to the specialized investments required for service delivery (Brown & Potoski, 2005). They can be considered sunk costs since users have to expend similar time and effort to switch to alternatives (Jones, Mothersbaugh, & Beatty, 2002). The investment for a particular transaction, in terms of time and effort, reflects the construct of asset specificity (Devaraj et al., 2006). Brown (2008) argued that asset specificity can be considered a service-specific factor that represents the specialized investment required for service delivery. Furthermore, both service-specific investments and asset specificity give rise to lock-in effects. Kim and Son (2009) used service-specific investments to explain why online consumers may continue to use the same service once they feel locked in. Devaraj et al. (2006) posited that asset specificity results in safeguarding, thereby leading to lock-in effects. Based on these perspectives, this study assumed that asset-specific investment can be adopted to represent service-specific investment because service-specific investment is similar to the intangible investment of asset specificity. Kim and Son (2009) further conceptualized service-specific investment as personalization and learning. Following Kim and Son (2009), this study adopted personalization and learning to represent asset specificity.

Personalization is defined as "the ability to provide content and service that are tailored to individuals based on knowledge about their preferences and behaviors" (Adomavicius & Tuzhilin, 2005, p. 84). Firms collect consumers' personal data, which they convert into a user model that informs subsequent actions taken to satisfy consumers' needs (Vendemia, 2017). Personalization systems infer consumers' preferences by collecting data and offer consumers the adaptively targeted content (Ashman et al., 2014). With respect to the context of this study, Airbnb adopts a matching system that gathers guests' travel and lifestyle preferences and uses them to connect the guests with compatible hosts and personalized services (Zhang L, 2018). Personalization offers consumers tailored information and thus creates memorable experiences. Consequently, personalization disincentivizes users from switching to alternatives and can thus be considered an asset-specific investment in the use of digital sharing platforms. In this study, personalization was defined as the extent to which a service provided by hosts can be tailored to a guest's activities, preferences, interests, and needs.

Personalization provides benefits to consumers; for instance, it helps customers perform some tasks better (Ashman et al., 2014). It also allows consumers to minimize the input or cost incurred or maximize the output in an efficient production process (Zhang, Agarwal, & Lucas, 2011). Moreover, for customers, personalization creates switching barriers or lock-in effects because they expect a new provider to offer the same level of tailored service (Kim & Son, 2009). Consumers are thus exposed to fewer alternative patterns under personalized services (Ashman et al., 2014). In addition, personalization is expected to affect transaction costs (Chen & Hitt, 2002). For example, Vendemia (2017) suggested that personalization provides individuals with better matching information. Hence, a lack of personalization is expected to make consumers expend more time and effort searching for information, monitoring transactions, and adapting to changes. Therefore, this study proposed that the provision of personalized services by hosts decreases the amount of time and effort guests spend in completing transactions on Airbnb.

H*1*. *: Personalization of asset specificity exerts a positive influence on transaction costs.*

Learning represents the time and effort that individuals spend to acquire the skills or knowledge to use a new service effectively (Alba & Hutchinson, 1987). Learning is associated with an individual's capabilities and history of interactions with a service provider. The cost of learning includes the time required to evaluate new alternatives, to establish a new account for a new system, and to use new features effectively. Consumers must spend time and effort to become familiar with new procedures or routines, such as operating systems or user interfaces (Park & Koo, 2016). When the cost of learning is perceived to be high, consumers may decide to abandon the platform due to low perceived value (Dang, Zhang, & Morgan, 2017). Therefore, learning can be considered an additional investment in knowledge acquisition when using a new service (Yanamandram & White, 2010). In the context of this study, digital sharing platforms provide new services that differ from those of traditional online third-party travel agent platforms, and consumers must overcome barriers to their adoption through learning. In this article, learning refers to the time and effort that consumers spend to acquire new knowledge or skills to use Airbnb.

Dang et al. (2017) and Kim, Kang, and Jo (2014) argued that the costs of learning negatively influence perceived switching value. Anderson and Simester (2013) further determined that customer switching results in transaction costs. These findings jointly suggest that learning that reduces transaction efficiency may increase consumers' transaction costs. Zhang et al. (2011) further indicated that learning can increase consumers' knowledge of the product and that this knowledge reduces the amount of time and effort customers expend to search for products or adjust to a service provider. When consumers must devote time to learn how to make reservations on Airbnb, they may face difficulty in searching for options, and monitoring and adapting to the transactions. This leads to the following hypothesis:

H*2*. *: Learning of asset specificity exerts a positive influence on transaction costs.*

3.1.2. Uncertainty

Some studies have proposed subdimensions of uncertainty. Grover and Malhotra (2003) and Hsieh et al. (2016) categorized uncertainty as environmental and behavioral. Environmental uncertainty refers to the unpredictability and complexity of the environment, whereas behavioral uncertainty refers to the difficulty in monitoring a transaction's execution or evaluating the performance of a transaction partner. Teo and Yu (2005) classified the uncertainty encountered in online stores into four types: branding uncertainty, behavioral uncertainty, environmental uncertainty, and uncertainty of product performance. Devaraj et al. (2006) and Kanwal and Rajput (2016) emphasized behavioral uncertainty, whereas Saleh et al. (2015) and Yan and Kull (2015) focused on environmental uncertainty. Che et al. (2015) proposed that product uncertainty and process uncertainty are the primary dimensions of uncertainty. Product uncertainty describes the buyer's difficulty in predicting a transaction's outcome and the buyer's satisfaction with the product, whereas process uncertainty refers to the buyer's confidence in completing the transaction process.

Because the classification of uncertainty provided by Teo and Yu (2005) fit with the research setting of this study, this study adopted branding uncertainty and performance uncertainty as the two subdimensions of uncertainty. Behavioral uncertainty and environmental uncertainty were excluded for the following reasons. First, behavioral uncertainty focuses on products rather than services. The measurement items for behavioral uncertainty are focused on products attained through sale services. Because Airbnb is a platform offering services to connect hosts and customers, behavioral uncertainty was deemed inappropriate for the research context of this study. Second, environmental uncertainty focuses on changes to a web page. In the case of Airbnb, hosts can add information regarding their accommodations, but they cannot change the framing or layout of the web page. Therefore, environmental uncertainty also did not fit the research context of this study. Branding uncertainty refers to consumers' perceptions of the difficulty in confirming service providers' service, whereas performance uncertainty involves the difficulty in ascertaining service quality (Teo & Yu, 2005). In this study of Airbnb transactions, branding uncertainty was adopted to represent guests' difficulty in ascertaining the reputations of hosts, and performance uncertainty was adopted to represent guests' perceived difficulty in ascertaining the quality of Airbnb accommodations.

Uncertainty implies the need to protect transacting parties by safeguarding the contract, thereby raising the costs of writing up, monitoring, and enforcing the transaction (Teo & Yu, 2005). More specifically, greater uncertainty increases the required monitoring and haggling costs, leading to increased transaction costs (Hsieh et al., 2016). Furthermore, Coase (1937), Liang and Huang (1998), Pemer, Werr, and Bianchi (2014), and Henten and Windekilde (2016) suggested that uncertainty impedes transactions and thus leads to transaction-related costs in markets. Synonymous to a brand, a host with an excellent reputation offers consistency, certainty, and quality to customers. When consumers can make decisions more easily with reliable information from hosts, a decrease in branding uncertainty reduces the transaction costs.

H*3*. *: Branding uncertainty exerts a positive influence on transaction costs.*

Behavioral uncertainty creates a performance evaluation problem, causing consumers to struggle to identify the best deal among multiple choices (Devaraj et al., 2006). For instance, hosts may purposefully choose not to disclose tax charges until customers make a reservation. Consumers make decisions when they believe that the purchased product will perform well (Teo & Yu, 2005). If purchasing a product entails performance uncertainty, consumers must spend time and effort monitoring the transaction, thereby increasing transaction costs. Promsivapallop et al. (2015) argued that the challenge of measuring product performance increases transaction costs. Kim (2017) demonstrated that when the consequences of a decision are not fully predicted, coordination and monitoring costs increase as well as the probability of failure. When consumers cannot predict the quality of their accommodation, they must collect more lodging information to ensure that their needs can be satisfied (Nisar et al., 2020). The additional time and effort spent evaluating the possible quality of the Airbnb accommodations increase transaction costs, leading to the following hypothesis:

H*4*. *: Performance uncertainty exerts a positive influence on transaction costs.*

3.1.3. Transaction frequency

According to Williamson (1985), transaction frequency is a critical dimension used to describe transaction costs. Pemer et al. (2014) proposed that an increase in the number of transactions contributes to the cost savings resulting from purchasing formalization. Akbar and Tracogna (2018) suggested that transaction recurrence frequency influences the selection of the most efficient mode of governance, specifically leading to firms adopting the mechanism that is most appropriate for achieving cost efficiency. Saleh et al. (2015) proposed that the frequency of communication and exchange enhances knowledge acquisition and is mutually advantageous for all parties. Likewise, consumers' reactions to service instances are influenced by frequency (Nisar et al., 2020). High-frequency consumers accumulate relevant information from each transaction with hosts on Airbnb, and this knowledge helps customers reduce the amount of time and effort required to compare various accommodations and monitor contracts.

H*5*. *: Transaction frequency exerts a negative influence on transaction costs.*

3.2. TCT and network externalities

Although the transaction dimensions (asset specificity, uncertainty, and frequency) can be used to explain transactions, the influence of each dimension may vary depending on the transaction (Foss & Weber, 2016). This study explored transaction costs and their determinants on Airbnb by integrating network externalities with TCT. Such integration was an appropriate approach because networks mitigate information asymmetry between transaction partners by facilitating access to information, thus improving the ability of agents to act rationally and reducing opportunism by transaction partners (Priyanath, 2017). Opportunism and bounded rationality are two of the human behavioral assumptions of TCT (Williamson, 1985). Opportunism refers to acting deceptively and selfishly, which may occur when one takes advantage of a transaction partner who has incomplete or inaccurate information (Wu et al., 2014). Bounded rationality refers to the limited capability to gather and process information (Devaraj et al., 2006). Transaction costs result from asymmetric or incomplete information among transaction partners (Cordella, 2006). Because of asymmetric information, firms and individuals are unable to make rational decisions, and the transaction partners tend to behave opportunistically. Furthermore, TCT describes the efficiency of transactions (Kim, 2017). Having many users facilitates information sharing in a network and enables the efficient utilization of resources (Barolli, Fukuda, Barolli, & Takizawa, 2008). Therefore, this study proposed that network externalities facilitate users' information processing, thus directly or indirectly influencing transaction costs.

Network externalities are classified as direct or indirect (Lai, Wang, Hsieh, & Chen, 2007; C.P. Lin & Bhattacherjee, 2008; X. Lin, Fu, & Liu, 2018; Zhou, Li, & Liu, 2015; Zhou & Lu, 2011). Direct network externalities are centered on the benefits derived from new users and usually represent network size (Zhang, Li, Wu, & Li, 2017). For example, as the user base grows, users can build connections with potential participants and thus have access to a larger network. In this article, direct network externalities refer to the number of users on a sharing platform. In contrast, indirect network externalities refer to complementary services or products that are not directly derived from the number of users (Hsu & Lin, 2016). Perceived complementarity is a market-mediated effect that represents complementary products, services, or functions available to the users (Lin & Bhattacherjee, 2008; Zhou & Lu, 2011). For instance, the popularity of mobile phones promotes the development of various types of applications. Specifically, users may benefit not only from the increased number of users but also from complementary or compatible services or products (Chiu, Cheng, Huang, & Chen, 2013; Lin & Lu, 2011). Access to richer complementary information enables consumers to make decisions effectively (Yen, 2014). When more users adopt Airbnb to reserve accommodations, they can share information in virtual communities, such as Facebook fan pages. Consumers can also provide ratings and reviews on Airbnb. This additional information makes complementary services more available and thus helps consumers choose among their accommodation options. Therefore, in this study, perceived complementarity was used to represent the complementary information that consumers receive pertaining to Airbnb.

3.2.1. Direct network externalities: number of users

Contingency theory is applied to explore conditional associations between two or more independent variables constituting a dependent outcome (Kabadayi, 2011). Chircu and Mahajan (2006) proposed that contingency factors influence transaction costs in the electronics retail industry. They argued that the characteristics of shopping events, such as transaction frequency, interact with product characteristics, such as availability, thus influencing transaction costs. Similarly, this study proposed that the direct externality, namely, the number of users, interacts with transaction costs and thus influences behavioral intention.

Direct network externalities are associated with the number of users (Zhou & Lu, 2011; Zhou et al., 2015). In addition to process, quality, and product attributes, the number of users provides utility and benefits to consumers (Wu, Li, Lin, & Zheng, 2017). Those network benefits can be utilitarian benefits, such as the practical value generated from the main products, or hedonic benefits related to the experience of pleasure (Li, Wang, & Tan, 2018). In the context of this study, an expanded user base means that more hosts and guests are joining the network. When more hosts participate on Airbnb, consumers have greater opportunities to experience various types of accommodations. If consumers perceive low transaction costs on Airbnb and believe that they can benefit from the increased user base, they may decide to use the platform. Accordingly, when network externalities exist, the negative effect of transaction costs on behavioral intention is alleviated, which leads to the following hypothesis:

H*6*. *: Direct network externalities moderate the negative influences of transaction costs on behavioral intention.*

3.2.2. Indirect network externalities: perceived complementarity

Indirect network externalities represent complementary information consumers can receive. Network externalities make the information flow more efficient due to standardized communication protocols, business interfaces, and operational processes (Lai, Wang, Hsieh, & Chen, 2007; Wareham, Mathiassen, Rai, Straub, & Klein, 2005). As the number of users increases, consumers gather and share more information on the digital platform or within virtual communities. A greater volume of information flowing among customers benefits all customers through product choice suggestions and help in solving problems (Stanko, Bohlmann, & Molina-castillo, 2013). Furthermore, (Lai, Wang, Hsieh, & Chen, 2007) found that accelerated information flow significantly reduces information asymmetries. Palvia, Pinjani, Cannoy, and Jacks (2011) suggested that individuals collect and analyze information in response to uncertainty. Efficient information flow enables consumers to acquire knowledge regarding the price and quality of products. Moreover, ratings and reviews serve as signals that reduce information asymmetries (Andreassen et al., 2018). When a transaction is uncertain and ambiguous, rich information helps individuals reduce asymmetries when making decisions. Therefore, when Airbnb provides rich information, such as ratings and reviews about hosts and accommodations, consumers can rely on such knowledge to reduce information asymmetries and uncertainty.

H_7. *: Indirect network externalities exert a negative influence on uncertainty, in terms of branding uncertainty and performance uncertainty.*

3.3. Transaction costs and behavioral intention

Transaction costs influence the behaviors of the transacting parties (Fussell, Harrison-Rexrode, Kennan, & Hazleton, 2006). The costs related to organizing information and monitoring the contract induce the parties to make adjustments and adopt the appropriate behaviors (Aubert et al., 1996). In addition, Teo and Yu (2005) indicated that transaction costs can be used to explain how consumers purchase online. Wu et al. (2014) argued that decreasing searching costs increases consumers' repurchasing intention. Che et al. (2015) proposed that low transaction costs can create a lock-in effect that encourages consumers to revisit. When consumers associate low transaction costs with Airbnb, they are more likely to use the platform to reserve an accommodation. Accordingly, transaction costs influence consumers' behavioral intention.

H_8. *: Transaction costs exert negative influences on behavioral intention.*

In sum, this study explores transaction costs and their determinants in the sharing economy through integrating network externalities with TCT. This study first investigates transaction costs in the context of the sharing economy. In addition, the study elucidates the antecedents of transaction costs, in terms of asset specificity, uncertainty, and transaction frequency, and their influences on transaction costs. Finally, the study explores the influences of network externalities on consumers' behavioral intention. Fig. 1 displays the research model.

4. Methodology

4.1. Measurement development

The questionnaire in this study was primarily adapted from the literature to the extent possible. Because the original scales were developed in English with prevalidated items drawn from the literature, a backtranslation process was employed to create a translated version corresponding to the original (Brislin, 1986). The English and Chinese versions of the scales were compared by a bilingual management scholar, and minor revisions were consequently made to decrease discrepancies. The scale items for each construct are listed in the Appendix 2. All the items were measured using a seven-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

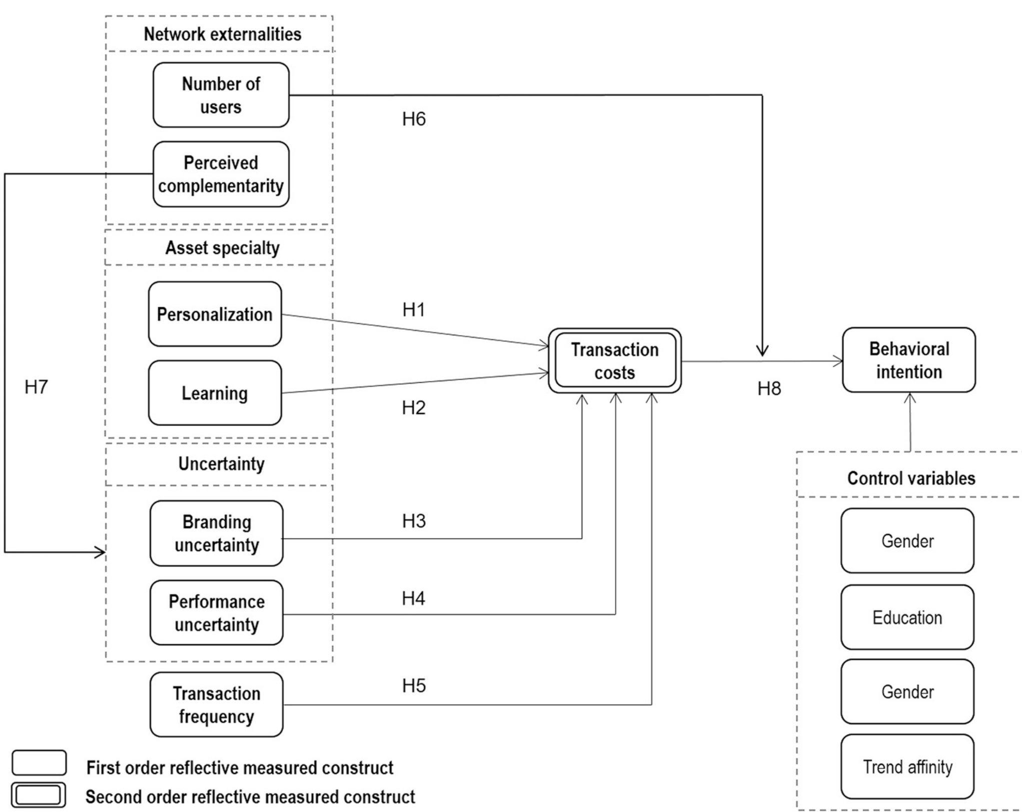

Fig. 1. The Research Framework of this Study.

4.2. Data collection and sampling

Because Airbnb is a website, data collection using an online questionnaire survey was an appropriate approach for reaching potential respondents. The respondents were invited to participate in the online questionnaire through a link posted to well-known travel and accommodation forums, including bulletin board systems, Facebook fan pages, chat rooms, and virtual communities. The survey's target subjects were customers who had used Airbnb to reserve an accommodation at least once. This study adopted convenience sampling for data collection. This approach involved nonprobability sampling, which was justified based on the lack of resources, inability to identify members of a population, and need to establish the existence of a problem (Henry, 1990). Because a reliable list of Airbnb users could not be obtained, it was impossible to conduct probability sampling. Given that users reserve rooms on Airbnb through its website, the use of an online survey was appropriate to reach potential respondents. Second, convenience sampling is a nonprobability sampling method that allows a researcher to access people who are knowledgeable about a particular issue (Cohen, Manion, & Morrison, 2007). This method enabled us to reach respondents who were familiar with the Airbnb platform. Third, convenience sampling is commonly used in peer-to-peer settings, such as Lin, Wang, and Wu (2017), Costa, Faria, and Vitória (2020).

Although convenience sampling provides access to a large number of individuals knowledgeable about a particular issue in a short period of time, it has some drawbacks (Costa et al., 2020). As suggested by Sedgwick (2013), convenience sampling may not contribute to external validity, although it does not threaten internal validity. External validity is defined as "the approximate validity with which we can infer that the presumed causal relationship can be generalized to and across alternate measures of the cause and effect and across different types of persons, settings, and times (Cook & Campbell, 1979, p. 37)," whereas internal validity represents "the approximate validity with which we infer that a relationship between two variables is causal or that the absence of a relationship implies the absence of cause (Cook & Campbell, 1979, p. 37)." Stated otherwise, external validity focuses on the generalizability of findings across times, settings, and individuals, whereas internal validity concerns causality.

The obvious drawback of convenience sampling is that it is likely to yield potential sources of bias (Farrokhi & Mahmoudi-Hamidabad, 2012). Presumably, survey participants are selected because they are accessible easily for the study. Given that convenience sampling uses arbitrarily selected participants, the sampling population is rarely representative of the general population (Hedt & Pagano, 2011). More specifically, not all eligible members of the population have equal opportunities to be selected, and thus the survey participant is susceptible to bias (Owen et al., 2014). However, Sedgwick (2013) posited that if the features of the recruited respondents represent those of the survey population, convenience sampling can generate useful data by addressing sample representatives to ensure external validity. If the sample representativeness is sufficient, the generalizability of the population supports external validity (Scandura & Williams, 2000). Selection bias should be carefully considered to ensure that sample is representative of phenomena (Abowitz & Toole, 2010; Skowronek & Duerr, 2009).

Assessing and controlling the representativeness of the respondents can reduce uncertainty when using convenience sampling (Skowronek & Duerr, 2009). A researcher should adopt a sample matching procedure for the predefined population of interest (Meyer & Wilson, 2009). In order to detect selection bias in this study, the following question was employed to separate users from nonusers: "Have you ever used Airbnb for accommodation reservation?" Furthermore, the profiles of the respondents were identified and compared with the characteristics of Airbnb users. According to iProperty (iProperty, 2019), approximately 54% of Airbnb guests are women, millennials account for nearly 60% of all guests, and approximately 60% of reservations are for an entire home. These data corresponded to our respondents' demographics and thus indicated sample representativeness.

Garcia and Pintrich (1995), Ferguson (2004), and Aguinis and Edwards (2014) noted that self-report questionnaires trade some internal validity for external validity. However, both external and internal validity are essential and crucial concerns in the research design (Sedgwick, 2013). Jimenez-Buedo and Miller (2010) suggested that internal validity is a prerequisite for external validity. After ensuing external validity by considering sample representativeness, this study carefully evaluated the possibility for internal validity. Accordingly, the scales of the questionnaire were constructed and administered to enhance internal validity and minimize the trade-off between internal and external validity. Precision in measurement instruments and careful construction of questions affect internal validity (Scandura & Williams, 2000). A well-designed questionnaire helps assure internal validity (Larson, 2005). Given that the convenience sampling was random and a literacy criterion was absent, a short and concise structured questionnaire was employed to avoid discrepancies in the responses and to increase content validity.

To reduce the occurrence of disingenuous responses, one set of identical but opposite question items (MC3 "I do not spend a lot of time monitoring whether the rooms I booked are ready") was integrated into the questionnaire. Furthermore, both a pretest and a pilot test were adopted to validate the instruments. As suggested by Burns and Bush (2013), a sample size of five to 10 respondents is appropriate for the evaluation of a survey questionnaire in a pretest. This study invited three management professors and three Airbnb hosts to discuss the appropriateness of the research questionnaire items. Based on their feedback and comments, minor changes, such as the length of the instrument, format, or wording of the scales, were made to each research construct to achieve a more logical sequence. The pretest was followed by a pilot test, which involved a convenience sample of 40 university students who had previously reserved accommodations on Airbnb. The final version of the questionnaire was then refined based on the feedback from the pilot test. The pilot test results indicated reliability (Cronbach's alphas 0.71–0.93), and the items loaded in the correct factor in the confirmatory factor analysis.

This study used the following two approaches to motivate individuals to participate in the questionnaire survey. First, the survey assured the respondents that the results would be anonymous and confidential. Second, participants were incentivized to complete the survey by offering a drawing with US$15 prizes and US$10 prizes. Participants interested in winning a prize were asked to provide their email addresses at the end of the survey. The online questionnaires were distributed from February 15 to April 15, 2018. After duplicates and incomplete responses were eliminated, 375 questionnaires remained for analysis. As shown in Table 1, the final sample comprised nearly equal proportions of male and female respondents. Most respondents (53.9%) were 25–34 years old. Approximately 86.4% of the respondents were unmarried, approximately 51.2% had university qualifications, and 41.6% were students. Approximately 57.8% had more than 2 years of experience of using Airbnb. The types of accommodations that the respondents typically chose to reserve were entire homes (58.4%), private rooms (25.1%), hotel rooms (13.3%), and shared rooms (3.2%).

This study used a nonresponse bias test and assessed common method bias to ensure data validity. First, the study tested for significant differences between respondents and nonrespondents to identify nonresponse bias by applying *t*-tests to the research variables. Per Armstrong and Overton (1977), the responses to each research construct in the early and late waves of returned surveys were compared. The findings demonstrated no statistically significant differences (at the 99% confidence interval) between the early-completing and late-completing groups. Therefore, the study sample was unaffected by significant nonresponse bias. Second, self-report data from a single source may result in common method bias. This study used the single-factor extraction test proposed by Harman (1967) to detect common method

Table 1
Demographic characteristics of the respondents.

Measure	Items	Frequency	Percentage
Gender	Male	190	50.67
	Female	185	49.33
Age	24 years old and below	64	17.07
	25–34 years old	202	53.87
	35–44 years old	90	24.00
	45–54 years old	17	4.53
	54 years old and over	2	0.53
Level of education	Senior high school and below	141	37.60
	University	192	51.20
	Graduate school and above	42	11.20
Marital Status	Unmarried	324	86.40
	Married	51	13.60
Occupation	Military personnel,	19	5.07
	government functionary, or	4	1.07
	teaching staff	45	12.00
	Agriculture, forestry, fisheries,	116	30.93
	or husbandry	12	3.20
	Manufacturing industry	10	2.67
	Business or service industry	156	41.60
	Freelance	13	3.47
	Homemaker		
	Student		
	Other		
Types of accommodation	Entire homes	219	58.40
	Private rooms	94	25.07
	Hotel rooms	50	13.33
	Shared rooms	12	3.20
Airbnb experience	Less than 6 months	34	9.07
	6 months- 1year	46	12.27
	1 year- 2 years	78	20.80
	2-years- 3 years	140	37.33
	More than 3 years	77	20.53

bias. When one method factor explains more than 50% of the variance among the instrument variables, common method bias exists (Podsakoff & Organ, 1986). On the basis of a principal component analysis of all the items, 10 factors explaining 75.28% of the variance were extracted, and the first factor only accounted for 10.35% of the variance. Because no single factor accounted for the majority of the variance, common method bias was not a serious concern in this study.

5. Data analyses and results

5.1. Measurement model

This study conducted partial least squares regression analyses with SmartPLS 3.2.3 to analyze the data (Ringle, Wende, & Becker, 2015) and used a two-step approach to evaluate the reliability and validity of the measurement scales and further test the hypotheses regarding the structural model framework (Anderson & Gerbing, 1988). The reliability of a construct is assessed using factor loading and composite reliability (CR) (Hair, Hult, Ringle, & Sarstedt, 2017). Item reliability is indicated when the loading of the measurement item on the intended construct is ≥ 0.7 (Chin, 1998). Due to the nonsignificance of its factor loadings, one item from the performance uncertainty construct (PU2) was deleted. Attaining a CR score greater than the cut-off of 0.7 indicates construct reliability (Chin, 1998). As shown in Table 2, the loadings of all items on their respective constructs were above 0.7, and the CR of all constructs surpassed the threshold value of 0.7, indicating the reliability of the model at the item and construct levels.

Both convergent validity and discriminant validity were assessed to ensure construct validity. To verify convergent validity, the average variance extracted (AVE) of each construct must be greater than the cut-off value of 0.5 (Henseler, Ringle, & Sarstedt, 2016). As illustrated in Table 2, all AVEs exceeded the threshold value of 0.5, meeting the condition for convergent validity of the research construct. Furthermore, two methods were applied to evaluate discriminant validity. First,

Table 2
Factor loadings and reliability.

Construct	Loading	T Statistics	CR[a]	AVE[b]
First order reflective construct				
Personalization			0.91	0.71
PE1	0.87	52.86		
PE2	0.84	35.47		
PE3	0.83	31.64		
PE4	0.83	34.33		
Learning			0.89	0.73
LE1	0.80	25.38		
LE2	0.91	80.29		
LE3	0.85	47.73		
Branding uncertainty			0.94	0.83
BU1	0.84	36.90		
BU2	0.95	180.67		
BU3	0.93	98.88		
Performance uncertainty			0.95	0.90
PU1	0.95	111.66		
PU3	0.94	63.51		
Transaction frequency			0.84	0.72
TF1	0.92	26.62		
TF2	0.78	12.18		
Searching costs			0.93	0.81
SC1	0.89	69.12		
SC2	0.90	73.99		
SC3	0.90	61.51		
SC4	0.85	40.17		
Monitoring costs			0.93	0.78
MC1	0.87	47.93		
MC2	0.87	62.93		
MC4	0.91	89.32		
Adaptation costs			0.91	0.78
AC1	0.88	63.64		
AC2	0.89	58.95		
AC3	0.93	89.82		
Number of users			0.92	0.80
NU1	0.86	3.71		
NU2	0.86	3.71		
NU3	0.97	3.59		
Perceived complementarity			0.93	0.83
PC1	0.89	16.31		
PC2	0.92	34.00		
PC3	0.92	25.41		
Behavioral intention			0.96	0.89
CI1	0.96	170.35		
CI2	0.94	94.43		
CI3	0.93	68.10		
Second-order reflective construct				
Switching costs			0.93	0.56
Searching costs	0.87	64.77		
Monitoring costs	0.80	33.92		
Adaptation costs	0.82	35.89		

Note: 1. [a.]CR, composite reliability; [b.]AVE, average variance extracted
2. Thresholds for each criterion: loadings> 0.7; CR> 0.7; AVE> 0.5 (Hair et al., 2019).

the correlations between the major constructs were calculated. When the square root of each AVE exceeds the correlation with other latent variables, discriminant validity is achieved (Fornell & Larcker, 1981). Second, the Fornell–Larker criterion and heterotrait–monotrait ratio of correlation (HTMT) criterion obtained for each construct should be under the predefined threshold of 0.85 to indicate discriminant validity (Ringle et al., 2015). As depicted in Table 3, the square roots of the AVEs were greater than all interconstruct correlations, and each HTMT criterion exceeded the recommended criterion of 0.85, indicating that all the pairs met these requirements. Thus, each of the main constructs measures a unique aspect and thus possesses sufficient discriminant validity.

5.2. Structural model

This study employed bootstrapping with 5000 resamples to generate standard errors and *t* statistics to test the hypotheses following Hair et al.

Table 3
Correlations among major constructs.

Variable	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)
(a) Personalization	**0.84**	0.23	0.38	0.40	0.22	0.35	0.39	0.38	0.32	0.35	0.19
(b) Learning	-0.21	**0.85**	0.55	0.37	0.17	0.67	0.57	0.46	0.21	0.12	0.13
(c) Branding uncertainty	-0.34	0.48	**0.91**	0.43	0.36	0.49	0.70	0.42	0.40	0.16	0.22
(d) Performance uncertainty	-0.36	0.32	0.38	**0.95**	0.23	0.41	0.54	0.41	0.33	0.20	0.19
(e) Transaction frequency	0.18	-0.12	-0.27	-0.17	**0.85**	0.26	0.45	0.33	0.04	0.61	0.73
(f) Searching costs	-0.31	0.58	0.45	0.37	-0.20	**0.90**	0.63	0.67	0.31	0.23	0.19
(g) Monitoring costs	-0.34	0.48	0.62	0.48	-0.35	0.55	**0.88**	0.58	0.43	0.32	0.46
(h) Adaptation costs	-0.34	0.39	0.38	0.36	-0.25	0.60	0.50	**0.88**	0.25	0.32	0.32
(i) Number of users	-0.28	0.20	0.36	0.31	-0.04	0.28	0.38	0.22	**0.89**	0.09	0.07
(j) Perceived complementarity	0.31	-0.12	-0.16	-0.19	0.50	-0.22	-0.29	-0.30	0.09	**0.91**	0.70
(k) Behavioral intention	0.18	-0.12	-0.22	-0.17	0.59	-0.18	-0.41	-0.30	-0.10	0.64	**0.94**

Note: 1. Diagonal elements are the square root of average variance extracted (AVE) of the reflective scales. Off-diagonal elements are correlations between construct. Above the diagonal element are the HTMT values.
2. Discriminant validity is achieved, if the square root of each AVE exceeds the correlation with other latent variables (Fornell & Larcker, 1981).
3. Thresholds for each criterion: HTMT < 0.85 (Hair et al., 2019).

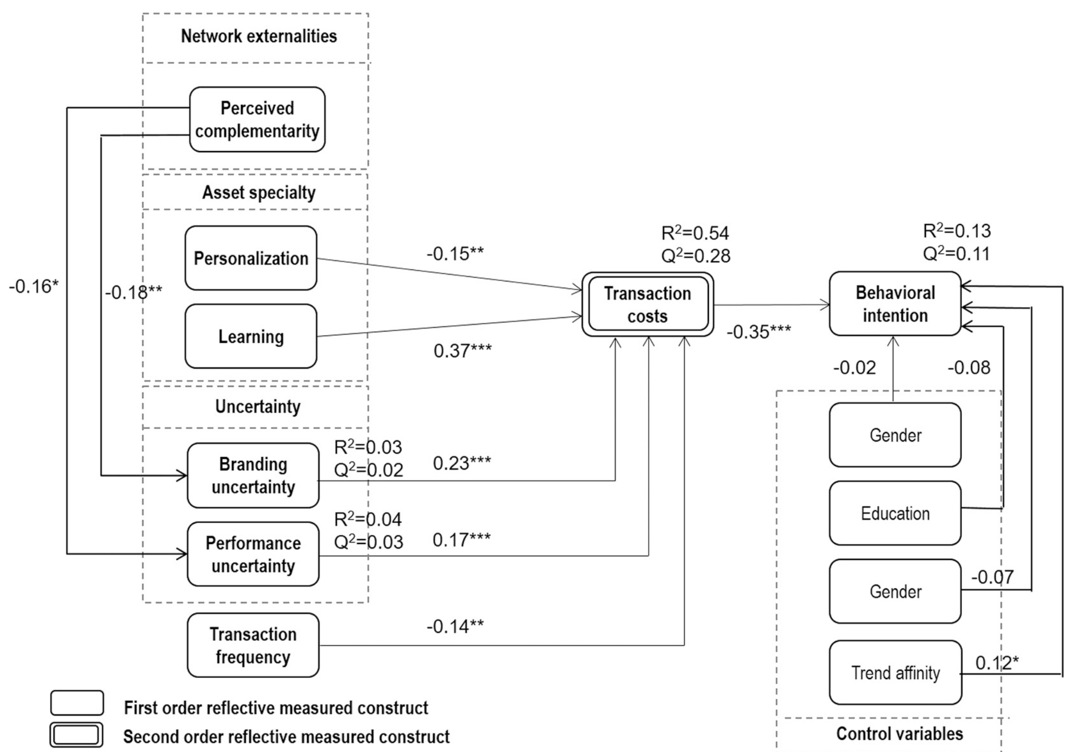

Fig. 2. PLS Results for the Proposed Model. Note: * $p < 0.05$, * * $p < 0.01$ * ** $p < 0.001$.

(2017). Fig. 2 displays the results of the assessment of the structural model. The research model indicated that the percentages of variance explained (R^2) of transaction costs, behavioral intention, performance uncertainty, and branding uncertainty were 54%, 13%, 4%, and 3%. This study further adopted cross-validated redundancy index (Q^2) tests to evaluate predictive relevance (Hair et al., 2017). The Q^2 values for the endogenous latent variables were all greater than 0. A fit index of the standardized root mean square residual (SRMR) was also applied for the composite factor model (Henseler, Ringle, & Sarstedt, 2015). The SRMR of 0.079 was below the cut-off value of 0.08, indicating that the model had good fit.

Fig. 2 shows that learning ($\beta = .37$, $p < .001$), branding uncertainty ($\beta = .23$, $p < .001$), and performance uncertainty ($\beta = .17$, $p < .001$) exerted positive influences on transaction costs, whereas personalization ($\beta = -.15$, $p < .01$) and transaction frequency ($\beta = -.14$, $p < .01$) exerted negative effects on transaction costs. Hence, H_1 to H_5 are supported. Furthermore, perceived complementarity exerted a negative influence on branding uncertainty ($\beta = -.18$, $p < .05$) and performance uncertainty ($\beta = -.16$, $p < .01$). Moreover, transaction costs had a negative effect on behavioral intention ($\beta = -.35$, $p < .001$). Thus, H_7 and H_8 are supported.

To examine the moderating role of direct network externalities (number of users) in the relationship between transaction costs and behavioral intention, multigroup analysis (MGA) was employed. Specifically, this study examined whether estimates of the same path of the direct network externalities obtained from the two groups (high and low) significantly differed. Following Aiken and West (1991), the high versus low groups were distinguished by a threshold of one standard deviation above the mean. Assessing the measurement invariance of composite models (MICOM), which is adopted to ensure that specific-group differences do not influence the results for latent variables, is a necessary step before conducting MGA (Henseler et al., 2016). The permutation test was used with 5000 permutation runs at a two-tailed 0.05 significance level. First, configural invariance was established. Second, the compositional invariance of the research model was verified. As illustrated in Table 4, there was no c significantly different from 1. In the final step (3a and 3b), the equality of means and cross-group variances were evaluated. The means and variances of the two groups did not differ considerably.

In conclusion, the full measurement invariance for the two groups was supported by the MICOM analysis and indicated the applicability of the MGA. As shown in Table 5, the number of users moderated the influence of transaction costs on behavioral intention ($\beta_{\text{high}} = -.427$, $\beta_{\text{low}} = -.209$, $p < .05$). Furthermore, both the t parametric (EV) and the Welch–Satterthwait test—t parametric (NEV)—yielded similar results to the parametric approach.

6. Discussion

TCT and network externalities were integrated to explore why consumers use Airbnb, and the following findings were obtained. First, consumers perceive different costs corresponding to the transaction, and they may relate to searching for relevant services, ensuring the terms of the contract, and securing postcontractual support for services. Asset specificity in terms of personalization and learning significantly affects transaction costs. When consumers receive services tailored to their preferences or can spend less time and effort acquiring skills or knowledge to transact on Airbnb, the burden involved in searching for information or monitoring or adapting to the transactions is reduced or eliminated. This finding is consistent with previous studies. Chen and Hitt (2002) proposed that personalization is associated with transaction costs, and Dang et al. (2017) posited that high learning costs may force individuals to not adopt an information system.

Second, branding uncertainty and performance uncertainty positively influence transaction costs. When a brand offers inconsistent quality or if the quality of its products cannot be ascertained, consumers' transaction costs increase. This finding accords with that of Hsieh et al. (2016), who demonstrated that greater uncertainty increases transaction costs. Third, transaction frequency negatively affects transaction costs. Consumers with more transaction experiences are likely to perceive transaction costs to be low. This finding is similar to that of Hsieh et al. (2016), who demonstrated that the number of transactions influences the type of transactions in which consumers engage. Furthermore, transaction costs positively influence behavioral intention. Consumers perceive a transaction to entail various costs, including searching for relevant services, ensuring the terms of the contract, and securing postcontractual support for services. High transaction costs prevent consumers from feeling confident in their purchasing decisions. This finding is consistent with the argument of Wu et al. (2014) that consumers evaluate transaction costs when making repurchasing decisions.

Table 4
MICOM of the MGA for number of users.

Composite (step 2)	C value[a]	95% confidence interval	Compositional invariance?
Transaction costs	0.999	[0.999; 1.000]	Yes
Behavioral intention	0.999	[0.999; 1.000]	Yes
Composite (step 3a)	Difference of the composite's mean value (=0)[2]	95% confidence interval	Equal mean values?
Transaction costs	0.190	[− 0.214; 0.213]	Yes
Behavioral intention	0.058	[− 0.210; 0.202]	Yes
Composite (step 3b)	Difference of the composite's variance ratio (=0)[b]	95% confidence interval	Equal variances?
Transaction costs	0.256	[− 0.302; 0.316]	Yes
Behavioral intention	0.275	[− 0.332; 0.327]	Yes

[a] Note: No C value significantly different from 1, showing the compositional invariance was verified (Henseler et al., 2016).

[b] The means and variances of the two group did not differ, indicating that the applicability of the multigroup analysis (Henseler et al., 2016).

Finally, the perceived complementarity of network externalities positively influences branding uncertainty and performance uncertainty. When consumers can receive complementary services or functions, their perceptions of risk related to hosts and accommodations are reduced due to the additional benefits attained from using Airbnb. This finding is consistent with that of Palvia et al. (2011), who proposed that collecting information helps individuals respond to uncertainty. Furthermore, the number of users moderates the relationship between transaction costs and behavioral intention. According to Strader (2017), the presence of more users constitutes a source of value to consumers using transaction-based online services. When many users participate in Airbnb, the negative impact of transaction costs on behavioral intention is attenuated. Specifically, when consumers perceive high levels of transaction costs and a small user base on Airbnb, they are more likely to switch to alternatives. This result reflects the findings of Zhou et al. (2015), who suggested that expanding the user base of a platform increases its perceived usefulness and switching costs. This result also echoes the findings of Kim and Min (2015), who suggested that Internet services exhibit strong network effects and that the number of users influences users' decisions.

6.1. Theoretical contributions and implications

This study differs from previous studies in three critical respects. First, the sharing behavior enabled by peer-to-peer software technologies is a phenomenon that has accelerated in the decades following the turn of the millennium (Amirkiaee & Evangelopoulos, 2018). Relevant studies have explored the impact of the sharing economy on consumers by applying the theory of planned behavior (Roos & Hahn, 2019), theory of reasoned action (Barnes & Mattsson, 2017), technology acceptance model (Min, So, & Jeong, 2019), unified theory of acceptance and use of technology (Lin et al., 2017; Tamilmani et al., 2020), complexity theory (Xue, Lu, Shi, & Yang, 2018), signaling theory (Zhao & Rahman, 2019), social exchange theory (Xu, 2020), social support theory (Nadeem et al., 2020), and social capital theory (Kim, Lee, Koo, & Yang, 2018), but peer-to-peer sharing has significantly altered behavioral patterns by reducing transaction costs. For example, Henten and Windekilde (2016) argued that consumers transacting in the commercial sharing market bear costs, including searching, contacting, and contracting costs. Geissinger, Laurell, and Sandström (2020) posited that the sharing economy offers flexible utility to customers, thus reducing transaction costs relative to conventional sharing. In this regard, TCT has been used to study many research topics, including joint ventures (Xue et al., 2018), strategic alliances (Kim, 2017; Pathak, Ashok, & Tan, 2020), finance (Chen et al., 2017), marketing (Che et al., 2015; Teo & Yu, 2005; Wu et al., 2014), innovation (Hsieh et al., 2016), outsourcing (Aubert et al., 1996; Promsivapallop et al., 2015), and information systems (Bugshan et al., 2014; Zhang X, 2020). In particular, Devaraj et al. (2006) argued that TCT could be applied to evaluate transactions in various settings, especially in online transactions. Xu (2020) further posited that the TCT framework can be applied in the context of the sharing economy, a contention with which other scholars agree (Akbar & Tracogna, 2018; Henten & Windekilde, 2016). By employing TCT, this study systematically explored the transaction costs associated with sharing platforms, thus addressing the research gap identified by Akbar and Tracogna (2018), who recommended applying TCT to the emergent domain of sharing platforms because "this new domain of research has a relatively limited extant literature (both theoretical and empirical)" (p. 99).

Table 5
Multigroup comparison test results.

Relationships	Low	High	Differences (High-Low)	$t_{parametric}$ (EV)[a]	$t_{parametric}$ (NEV)[a]	Permutation p-values	Significance
Moderator: number of users							
Transaction costs- Behavioral intention	-0.427	-0.209	0.217	2.006	2.013	0.025	**Yes**

[a] Note: Moderating effect is confirmed, when $t_{parametric}$ (EV) and $t_{parametric}$ (NEV) are significant (Henseler et al., 2016).

Second, although TCT offers a theoretical foundation for studying transaction costs, it does not mandate fixed factors for the antecedents of transaction costs. For example, Che et al. (2015) used unpredictability to represent uncertainty and adopted trust and personalization specificity to represent asset specificity. Promsivapallop et al. (2015) categorized uncertainty as environment uncertainty and behavioral uncertainty. Teo and Yu (2005) replaced asset specificity with trust, defined in terms of dependability and privacy policies. Following Williamson (1981), this study articulated three key antecedents of transaction costs in the context of the sharing economy: asset specificity, uncertainty, and transaction frequency. In particular, this study adopted service-specific investments, including personalization and learning, to represent asset specificity because tangible assets (mobile applications or websites) that consumers use to access a sharing platform can be used for other purposes. Devaraj et al. (2006) argued that the time and effort spent on a particular transaction constitute asset specificity. Given that consumers must expend time and effort to complete transactions, this study assumed that, conceptually, service-specific investments are similar to the intangible investments constituting asset specificity. This study corroborated the findings of Large (2011), who argued that "transaction cost theory predicts the existence of specific investments by the providers" (p. 39). Hence, this study bolsters the case for the theoretical applicability of the TCT framework by filling the gaps in the research concerning transaction costs in the context of the sharing economy.

Finally, the benefits of network externalities can be achieved through the use of sharing economy platforms (Bauer & Gegenhuber, 2015). The increasing user base on Airbnb provides opportunities for consumers to communicate with other users and find more suitable accommodations from among a large group of participants. Although sharing platforms are subject to network effects, few studies have explored how the size of the network of a certain platform increases its value. Because platforms connect buyers and sellers, network externalities offer utility to users directly based on the number of users and indirectly based on complementary services (Tseng & Teng, 2014). This study explored the effects of network externalities on consumers' intention to use Airbnb in response to the observation of Stanko et al. (2013) that "network externalities have perhaps received the most attention, but the conclusions are mixed as to whether and when a firm can benefit from strong network effects" (p. 650). This study contributes to the theoretical literature by integrating TCT with network externalities in the context of the sharing economy.

6.2. Implications for practice

Sharing economies that include the peer-to-peer sharing of products or services can be considered a socioeconomic phenomenon (Botsman & Rogers, 2010). This study facilitates a comprehensive understanding of this phenomenon among practitioners from the viewpoint of transaction costs. First, for consumers, personalization and transaction frequency reduce the perceived transaction costs associated with using Airbnb. Personalization involves displaying consumers' buying habits in a profile that facilitates their decision-making. Additionally, personalization is associated with privacy because the personalization process entails collecting user information to predict their preferences. Although personalization may benefit consumers by reducing transaction costs, data should only be collected with consumers' permission to allay their privacy concerns. Furthermore, experienced consumers perceive lower transaction costs associated with using Airbnb. Market segmentation and position strategies help firms target and attract the right consumers. Maintaining relationships with customers is essential for firm survival. Conversely, a firm may monitor customers' transaction records with respect to data on, for example, the recency, frequency, and amount of money spent to ensure that resources are optimally allocated to customers.

Second, learning and uncertainty increase consumers' transaction costs. The sharing economy has redefined the idea of ownership by changing the nature of how services or products are accessed (Leung, Xue, & Wen, 2019). If consumers must invest additional time and effort in learning relevant functions and obtaining specific knowledge, their interest in using Airbnb will be reduced. Thus, managers must design a useful and user-friendly system by emphasizing a simple and aesthetically engaging interface. For instance, the consumer should be able to find information intuitively and transfer data easily from other service systems. Moreover, both branding uncertainty and performance uncertainty influence transaction costs. Notably, branding uncertainty was more influential on transaction costs ($\beta = 0.23$) than performance uncertainty ($\beta = 0.17$). We infer that the quality of accommodations can be considered a basic feature that customers expect from the service, whereas the branding of the hosts can be considered a surprise element that makes the service more competitive. This finding is particularly valuable for service providers on the sharing platform because the branding evaluation of the hosts is more important than the performance evaluation of the accommodations for reducing transaction costs. In addition to offering evidence of the quality and safety of their services and products, managers should focus more on guaranteeing brand reputation and providing consistent branding messages. For example, managers may provide incentives (e.g., coupons) to motivate customers to give their opinions on their brand or services through rating, reviewing, and recommendation mechanisms. Rich information about the branding or performance of services or products reduces consumers' searching, monitoring, and adaptation costs.

Third, the indirect network externality of perceived complementarity reduces consumers' uncertainty perceptions regarding Airbnb. The availability of complementary functions or tools, such as photo sharing or recommendation mechanisms, increases information richness. When consumers can gather and interact on social media to obtain or exchange information (Abed, Dwivedi, & Williams, 2015; Dwivedi, Ismagilova, Hughes, Carlson, Filieri, Jacobson, & Wang 2021a; Dwivedi, Ismagilova, Sarker s, Jeyaraj, Jadil, & Hughes 2021b) without geographical constraints, the convenience of communication and increase in information richness reduce their concerns about accommodations. Firms must not only formally maintain the brand–customer relationship but also provide complementary functions or services that facilitate consumer interaction. For example, firms can launch blogs or forums that facilitate social interactions between customers with similar interests or preferences. Furthermore, the direct network externality of the number of users moderates the relationship between transaction costs and behavioral intention. As more service providers or consumers join a platform, the availability of products or services increases, indicating a greater possibility of satisfying consumers' needs. When consumers perceive that numerous consumers are using Airbnb, the negative impact of transaction costs on behavioral intention is mitigated. Although utilizing marketing strategies to expand a user base is not a simple task, managers must continually strive to attract new consumers because new consumers make the network larger and thus more attractive.

6.3. Limitations and future research directions

The findings of this study are useful for managers, especially in the hotel industry, in developing new businesses that follow the trends of the sharing economy. However, as with most empirical studies, this study is not without limitations. Airbnb was the research context of this study. The sharing economy involves several types of behaviors and activities, whether commercial or noncommercial (Henten & Windekilde, 2016). Each form of sharing has features that are increasingly unique to its industry due to specialization. For instance, both Airbnb and Uber belong to the sharing economy, but Airbnb has spread around the world, whereas Uber has been tightly regulated or banned in many countries. Thus, in future studies, scholars may wish to focus on different contexts of sharing to reduce variances.

Second, the uniqueness of a specific research setting impairs the accurate identification of causal relationships thereby hampering causal inference (Feldon & Yates, 2007). In particular, this study determined the relationships of the research constructs in the context of Airbnb. Whether the research findings can be generalized to other research contexts, such as Uber, requires further verification. Some studies have explored strategies to minimize the trade-off between internal and external validity. For instance, Ferguson (2004) argued that researchers can enhance external validity by controlling moderating factors while addressing internal validity by ensuring representativeness. Feldon and Yates (2007) suggested that combining various research designs alleviates the tension between achieving internal validity from laboratory-based methods and external validity from field-based ones. Aguinis and Edwards (2014) contended that implementing novel research designs, such as introducing virtual reality, strikes a balance in this trade-off between internal and external validity. Therefore, future studies may employ novel research designs involving advanced technologies or combining various research designs to minimize the trade-off between interpretability (internal validity) and generalizability (external validity).

Third, TCT is a useful model for explaining why consumers prefer the channel with the lowest transaction costs (Teo & Yu, 2005). This study employed TCT to understand the antecedents of the transaction costs of sharing platforms. However, various types of factors create transaction costs in the economy (Henten & Windekilde, 2016). Future research may incorporate other predictors into the models to describe transactions in the context of the sharing economy. Fourth, this study adopted convenience sampling for data collection, which is a nonprobability sampling method employed when randomization is impossible. The probability of a person in a desired population being selected into the sample is unknown, thus resulting in sampling bias and decreasing the generalizability of the findings (Etikan, Musa, & Alkassim, 2016). Future studies could use probability sampling techniques to eliminate potential sampling bias or replicate studies with different formats to ensure generalizability.

Fourth, this study was only conducted in Taiwan due to time and budget limitations. Cross-cultural factors could be included in future studies to make the results more generalizable. Future studies could validate this model by collecting data from other developed economies as well as from emerging and developing economies. Finally, as suggested by Dwivedi et al. (2022), articles are likely to be desk rejected, while examining intention with cross-sectional data which neglects usage or behavior aspect. Future studies could consider evaluating consumers' actual usage instead of intention.

7. Conclusions

Although sharing has been common throughout human history, the sharing economy has arisen with the development of digital platforms and large-scale mediating technologies that facilitate sharing behavior (Sutherland & Jarrahi, 2018). In the context of the sharing economy, suppliers and consumers coordinate the acquisition and distribution of unutilized resources, with their activity mediated by the online platform. Coase (1937) stated that transacting in a market involves many costs. Information may not be fully disclosed in an online marketplace, implying that sharing behaviors involve asymmetric information and economic risks. Digital platforms must thus enhance transparency by reducing information asymmetries (Greenwood & Wattal, 2017). However, empirical assessments of transaction costs from the perspective of consumers in the commercial sharing economy are lacking. This study determined the effects of asset specificity, uncertainty, and transaction frequency on transaction costs. Moreover, perceived complementarity was determined to influence transaction uncertainty, whereas the number of users was determined to moderate the relationship between transaction costs and behavioral intention. The findings of this study can aid managers in numerous industries, especially the hotel industry, in coping with the trend toward the sharing economy.

CRediT authorship contribution statement

This manuscript is accomplished by the Chia-Ying Li and Yu-Hui Fang. Chia-Ying Li is responsible for data collection and draft writing, and Yu-Hu Fang is responsible for manuscript revision and future corresponding. The paper has not received prior publication and is not being considered for publication elsewhere.

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Appendix 1. : Overview of Relevant Literature on Airbnb

Author	Research objective	Research type/ Variables	Research context
Yannopoulou, Moufahim, and Biran (2013)	Understanding the brand identity construction of user-generated brands	Discursive and visual analysis	Airbnb and Couchsurfing
Möhlmann (2015b)	Developing a framework on the determinants of choosing a sharing option	Quantitative study/ Independent variables: community belonging, cost savings, environmental impact, familiarity, internet capability, service quality, smartphone capability, trend affinity, trust, utility Dependent variables: satisfaction, likelihood of choosing a sharing option again	Car2go and Airbnb
Foss and Weber (2016)	Identifying the success of Airbnb and analyzing its business model	Conceptual research	Airbnb
	Exploring different forms of internet-based platform services	Case analyses	Airbnb, Uber

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Author	Research objective	Research type/ Variables	Research context
Henten and Windekilde (2016)			
Hawlitschek, Teubner, and Weinhardt (2016)	Proposing a model delineating trust in customer to customer markets	Questionnaire survey/ Independent variables: trust Dependent variables: behavior intention	Airbnb
Bae et al. (2017)	Discussing pretrip decision-making and posttrip behavior of travelers' use of shared experiences	Questionnaire survey/ Independent variables: social distance, breadth of shared experience, perceived information discrepancy, deviaion from neutral experience Dependent variables: credibility of shared expereicne, information usefulness, adoption of sahred experience, purchase intention, experience sharing	Airbnb
Lin et al. (2017)	Exposing Airbnb use behavior	Questionnaire survey/ Independent variables: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit Dependent variables: behavior intention, use behavior	Airbnb
Zervas, Proserpio, and Byers (2017)	Assessing the economic impact of the sharing economy on incumbent firms	Data from various websites regarding the case of Airbnb	Airbnb
Chen and Chang (2018)	Assessing the factors that influence the purchase intention of Airbnb users	Questionnaire survey/ Independent variables: rating, rating volume, review, information quality, media richness Dependent variables: perceived value, satisfaction, purchase intention	Airbnb
Laurell and Sandström (2018)	Understanding how social media are different from traditional media in coverage of disruptive technological change	Content analysis	Uber and Airbnb
Lutz and Newlands (2018)	Investigating consumer segmentation within Airbnb	A mixed-method approach: a quantitative survey of Airbnb users and followed with a qualitative content analysis of Airbnb listings	Airbnb
Magno, Cassia, and Ugolini (2018)	Assessing whether hosts dynamically adjust prices for shared accommodation based on their experience with price management and on the level of market demand	Questionnaire survey/ Independent variables: market demand, host experience, accommodation attributes Dependent variables: price	Airbnb
Mittendorf (2018)	Exploring the impact of trust on the obtainers' intentions to inquire about accommodations and to request a booking	Questionnaire survey/ Independent variables: familiarity with intermediary, disposition to trust Dependent variables: trust in the intermediary, trust in the provider, inquire about, active request	Airbnb
Sung, Kim, and Lee (2018)	Assessing the virtuous circulation of consumption for sustainability of sharing economy	Questionnaire survey/ Independent variables: travel host profiles, hybrid host profiles, worker host profiles Dependent variables: attitude, behavior intention	Airbnb
Zhang T.C (2018)	Proposing a framework for understanding the antecedents determining perceived trust	Quantitative analysis, text mining and face recognition	Airbnb
Cho, Park, and Kim (2019)	Exploring the impact of identity information on sharing economy platforms	Questionnaire survey/ Independent variables: identity information, peer reviews Dependent variables: social presence, trust, consumption intention	Airbnb
Clauss et al. (2019)	Assessing platform loyalty from a customer-centric perspective	Questionnaire survey/ Independent variables: customer assessment of value cocreation processes, customer assessment of value proposition design, customer assessment of value capture mechanisms Dependent variables: emotional vlaue, quality value, price value and loyalty	Airbnb, Blablacar, Shpock and Kleiderkreisel
Huarng and Yu (2019)	Investigating consumer behavior for the sharing economy in the hotel industry	Questionnaire survey/ Independent variables: service quality, lodging service quality, experience Dependent variables: satisfaction, continuous consumption behavior	Airbnb
Lee et al. (2019)	Exploring how attachment and ownership are formed within the sharing economy organizational structure	Questionnaire survey/ Independent variables: information sharing, empowerment, outcome expectations, self-disclosure, similarity, communication openness Dependent variables: attachment to Airbnb, attachment to peer hosts, psychological ownership, organizational citizenship behavior toward Airbnb, organizational citizenship behavior toward peer hosts	Airbnb
Newlands, Lutz, and Fieseler (2019)	Exploring how rating mechanisms encourage emotional labor norms among consumers	Questionnaire survey/ Independent variables: negative rating experience, rating literacy, rating process fairness, matching quality Dependent variables: expressive emotional labor	Airbnb, Uber, Lyft, Lending Club, Prosper
Ruihe, Zhang, and Yu (2019)	Exploring three categories of antecedents for hotels consumers' switching intention	Questionnaire survey/ Independent variables: push factors (service,	Airbnb

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Author	Research objective	Research type/ Variables	Research context
		decoration, amenity), mooring effect, pull factors (economic value, social benefit, hedonic value, epistemic value) Dependent variables: switching intention	
Zamani, Choudrie, Katechos, and Yin (2019)	Exploring how trust perceptions form and get communicated through sharing economy platforms	Data collected from online reviews	Airbnb
Zhang (2019)	Assessing customers' experiences and comparing the extracted topics from online reviews between Airbnb and the traditional hotel industry	Text-mining approaches, including content analysis and topic modeling	Airbnb
Zhao and Rahman (2019)	Exploring the effects of hosts' quality attributes on the reservation performance of their listings	Data collected from Inside Airbnb database/ Independent variables: host attributes quality (local host, super host, response rate, membership, verification), host attributes quality (listing number) Dependent variables: reservation in 1 month	Airbnb
Abdar and Yen (2020)	Exploring the implicit meaning of Points of Interest to finds out the correlations in between recommended spots and user preference	Computational techniques	Airbnb
Califf et al. (2020)	Comparing the effects of human-like trusting beliefs and system-like trusting beliefs on four outcome variables—enjoyment, usefulness, trusting intention, and continuance intention	Questionnaire survey Independent variables: human-like trusting beliefs, system-like trusting beliefs Dependent variables: enjoyment, usefulness, trusting intention, continuance intention	Airbnb and "traditional" online travel booking websites (e.g., Expedia.com)
Chang and Sokol (2020)	Examining the impacts of Airbnb on hotels' demand and price and non-price response strategies in Taiwan	Data collected from Operating Report of Tourist Hotels (ORTH) of Taiwan and the number of Taiwanese Airbnb listings from Airbnb.com	Airbnb
Chua, Chiu, and Chiu (2020)	Understanding the factors that influence travelers' trust to use Airbnb within the three ASEAN nations	Questionnaire survey Independent variables: ease of use, convenience, security, reputation, normative influence, informative conformity, trust Dependent variables: behavior intention	Airbnb
Costa et al. (2020)	Evaluating the importance of trust on the user's intention to buy, and the relevance of the comments for building trust	Questionnaire survey/ Research variables: trust	Airbnb
Cui, Li, and Zhang (2020)	Exploring ways to reduce discrimination using online reputation systems	Field experiments	Airbnb
Geissinger et al. (2020)	Identifying a long tail of 17 sectors and 47 subsectors in which a total of 165 unique sharing-economy actors operate	Drawing on data from social and traditional media in Sweden	Uber and Airbnb
Hong and Yoo (2020)	Exploring the spatially heterogeneous relationship between price and pricing variables	Multiscale Geographically Weighted Regression	Airbnb
Jun (2020)	Exploring the main effects of perceived risks, brand credibility and past experience on intention to stay at Airbnb places	Questionnaire survey Independent variables: perceive risk, brand credibility, past experience Dependent variables: intention to stay at Airbnb place	Airbnb
Kim and Kim (2020)	Considering social benefits, relative attractiveness, and price fairness as the key antecedents of calculative commitment	Questionnaire survey Independent variables: authentic experience, trust in Airbnb, social benefits, relative attractiveness, price fairness, affective commitment, calculative commitment Dependent variables: customer loyalty	Airbnb
Lang et al. (2020)	Exploring how one-sided users become prosumers	Questionnaire survey/ Independent variables: trust, gratitude Dependent variables: intention to become prosumers	Airbnb
Muller (2020)	Criticizing the current definition of disruption and offer one instead, followed by three recent examples - iPhone, Uber, and Airbnb	Discussion	Uber, Airbnb
Nadeem et al. (2020)	Investigating the antecedents of consumers value co-creation intentions at sharing economy platforms	Questionnaire survey/ Independent variables: social support Dependent variables: consumers' ethical perceptions, trust, satisfaction, commitment, value co-creation	Uber, Lyft, Airbnb, Indiegogo, Homeaway, Kickstarter, and Zipcar
Nisar et al. (2020)	Understanding the determinants that affect accommodation purchase intentions through lodging websites	Questionnaire survey/ Independent variables: perceived lodging value, perceived lodging price, lodging information, online lodging reviews, trust with the host, website usability, perceived privacy security Dependent variables: purchase intention	Lodging websites, such as Airbnb, housetrip and holidaylettings
Sutherland and Kiatkawsin (2020)	Analyzing the factors that drive customer experience and satisfaction within the sharing economy of the accommodation sector	Data collected from Inside Airbnb	Airbnb
Tamilmani et al. (2020)	Underscoring the central role of attitude that significantly mediates the effects of effort expectancy, social influence, and facilitating conditions on consumer intention to use Airbnb	Questionnaire survey/ Independent variables: social influence, performance expectancy, effort expectancy, hedonic motivation, facilitating conditions, self-efficacy, trust, attitude Dependent variables: behavioral intention	Airbnb
Thaichon et al. (2020)	Determining the factors that lead to host and guest satisfaction and value co-creation	Interviews	Airbnb
Xu (2020)			Airbnb

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Author	Research objective	Research type/ Variables	Research context
	Exploring consumers' perceptions and behavior based on their online textual reviews	Text -mining and text -regression approaches/ Independent variables: entire place, private room, and shared room Dependent variables: consumer demand of the attributes, customer satisfaction, product and service attributes	
Yi et al. (2020)	Elucidating how risks affect the diffusion of the sharing economy	Questionnaire survey/ Independent variables: attitude, subjective norm, positive anticipated emotion, negative anticipated emotion, perceived behavior control, physical risk, financial risk, privacy risk, performance risk Dependent variables: desire, behavior intention	Airbnb
Zhang and Fu (2020)	Examining the accommodation experience of Airbnb guests and comparing the accommodation experience perception between domestic Chinese and foreign English-speaking Airbnb guests	Text-mining techniques	Airbnb
Zhang X (2020)	Investigating the relationships among host self-description, trust perception and purchase behavior	A deep-learning-based method	Airbnb
Barnes (2021)	Exploring perceptions of facial trustworthiness overvalued in the evaluation of hosts on Airbnb	Public domain dataset and Convolutional neural networks Independent variables: perceived attractiveness, perceived trustworthiness, super host, review volume Dependent variables: overall rating	Airbnb
Barnes and Kirshner (2021)	Exploring market segment structure of sharing economy	Text-mining	Airbnb
Li, Li, Wang, and Yang (2021)	Investigating the impact of consumer animosity on outbound travelers' demand for sharing-based accommodations	Panel data set	Airbnb
Vieira, Pinto, Sugano, Carvalho, and Grutzmann (2021)	Analyzing how the network effect moderates the acceptance of a peer-to-peer application	Questionnaire survey Independent variables: price, network effect, value of hosting, number of users, value of hosting Dependent variables: behavior intention	Airbnb
Xu, Zeng, and He (2021)	Examining the role of information disclosure in influencing consumers' purchase behavior	A web crawler in Java	Airbnb

Appendix 2. Questionnaire used in this study

Asset specificity (adapted from Kim & Son, 2009)	**Mean**	**SD**
Personalization		
PE1 Airbnb is personalized in some way.	3.72	1.40
PE2 I set up Airbnb to use it the way I want to.	4.07	1.39
PE3 I have put effort into adapting Airbnb to meet my needs.	3.91	1.46
PE4 I have chosen features offered by Airbnb to suit my style of hotel booking.	4.43	1.36
Learning		
LE1 Learning to use the features offered by Airbnb took a lot of time and effort.	4.84	1.35
LE2 There was a lot involved for me to understand Airbnb well.	4.72	1.41
LE3 I spend a lot of time and effort to learn the booking procedure at Airbnb.	4.26	1.48
Uncertainty		
Branding uncertainty (adapted from Teo & Yu, 2005)		
BU1 It is difficult to determine whether hosts of Airbnb offer adequate information about available choices.	4.75	1.37
BU2 It is difficult to determine whether hosts of Airbnb provide sufficient information about available services.	4.33	1.44
BU3 It is difficult to determine whether hosts of Airbnb are easy to contact.	4.19	1.49
Performance uncertainty (adopted from Promsivapallop et al., 2015)		
PU1 It is difficult to determine whether the hotels on Airbnb will perform as well as they are supposed to.	3.61	1.47
PU2* It is difficult to determine whether the hotels on Airbnb will perform as well as others.	4.26	1.45
PU3 It is difficult to determine whether the hotels on Airbnb will comply with their established agreement.	3.70	1.40
Transaction frequency (adapted from Miranda & Kim, 2006**)**		
TF1 When I plan to travel, I use Airbnb frequently.	4.12	1.80
TF2 When I plan to travel, I do not usually use Airbnb.	3.98	1.73
Transaction costs (adapted from Teo & Yu, 2005**)**		
Searching costs		
SC1 I spend a lot of time looking for information before using Airbnb.	3.91	1.53
SC2 I spend a lot of effort getting information that would be helpful in decision-making when using Airbnb.	3.92	1.54
SC3 Usually there is so much to do that I wish I had more time to look for information before using Airbnb.	4.37	1.52
SC4 I usually find myself pressed for time in searching for information before using Airbnb.	4.78	1.53
Monitoring costs		
MC1 I spend a lot of time contacting hosts to check whether the rooms I booked are ready.	3.10	1.56
MC2 I spend a lot of effort contacting the hosts to check whether the rooms I booked are ready.	3.75	1.56
MC3* I do not spend a lot of time monitoring whether the rooms I booked are ready. (R)	2.85	2.03
MC4 I spend a lot of effort monitoring whether the rooms I booked are ready.	3.84	1.65
Adaptation costs		
AC1 It takes time and effort to make changes to the booking that was sent to Airbnb.	4.11	1.45
AC2 It takes time and effort to make changes to the booking when it is close to my arrival date.	4.94	1.35

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Asset specificity (adapted from Kim & Son, 2009)	Mean	SD
AC3 It takes time and effort to make any unexpected changes.	4.65	1.40
Number of users (adapted fromKim & Min, 2015)		
DN1 I think a good number of people use Airbnb.	3.52	1.57
DN2 I think many friends around me use Airbnb.	3.55	1.56
DN3 I think there will still be many people joining Airbnb.	3.12	1.55
Perceived complementarity (adapted fromLin & Lu, 2011)		
PC1 A wide range of social activities on social media (e.g., Facebook) can be joined (e.g., fan pages).	4.84	1.17
PC2 A wide range of supporting tools is available on Airbnb (e.g., photo sharing, message sharing, video sharing).	4.38	1.28
PC3 Diverse types of ratings and reviews, such as hosts and hotels, are available on Airbnb.	4.87	1.12
Behavioral intention (adapted fromTamilmani et al., 2020)		
BI1 I am likely to choose Airbnb next time.	5.10	1.24
BI2 In the future, I would prefer Airbnb to other alternatives.	5.21	1.25
BI3 it is likely that I will choose Airbnb in the future.	5.09	1.35

* Note: represents items that were deleted in the main study because their loadings were small and nonsignificant; (R) represents a reverse item.

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