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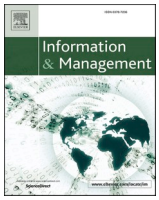

What drives consumers to adopt a sharing platform: An integrated model of value-based and transaction cost theories

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ABSTRACT

The sharing economy has become a source of innovation in recent years. However, some sharing business models succeed while others fail. A research model combining transaction costs and value-based models is developed and empirically evaluated using 476 responses. The results indicate that transaction costs and perceived benefits affect perceived value, which affects the intention to use the platform. The sharing object moderates the effect between transaction costs and perceived value. The effects of location and brand asset specificity on transaction costs vary across different sharing objects. Our findings explain why certain products are more likely to be successful on sharing platforms.

1. Introduction

Driven by the rapid proliferation of information and communication technology (ICT), the sharing economy has become an emerging trend that enables *sharing* to grow and empower transactions [1–3]. The European market scale of the five most prominent sharing economy sectors—collaborative finance, peer-to-peer accommodation, peer-to-peer transportation, on-demand household services, and on-demand professional services—is expected to grow from revenues of $31 (€28) billion in 2016 to around $633 (€570) billion by 2025 [4]. The sharing economy model has changed the way in which many services are provided. The sharing platform simplifies the process of providing services to the market and allows people to easily generate value from idle resources [1], also reflecting the concept of green consumption [5]. It is the interface that facilitates resource sharing between private parties. New ventures such as Uber and Airbnb have experienced notable success in matching suppliers and users [6]. However, building a successful sharing model is clearly challenging. Whereas Uber is still struggling with huge financial losses on its other business units, cases such as Neighborrow[1] and Homejoy[2] failed after burning through their angel money. Bike sharing in China also turned sour in early 2019 [7]. WeWork has encountered heavy losses and shows no evidence of turning around [8,9].

Why do certain platforms succeed while others fail? What factors drive the success of a sharing platform? We define "success" as the capability to provide services and attract users without reporting financial or other crises. A few studies discuss the motivations for user participation in sharing platforms and explore the factors behind user intentions to adopt such services. For instance, Mohlmann [10] finds that user self-benefits such as utility, trust, cost savings, and familiarity are the predominant determinants of adoption intention. Hamari et al. [11] use self-determination theory (SDT) to show that people are motivated by the sustainability of the sharing platform, enjoyment of the activity, and economic rewards. Tussyadiah [3] adopts social exchange theory (SET) to examine factors that influence user satisfaction and future intention to use the platform. She finds that enjoyment and economic benefits have a positive effect, whereas social benefits have a negative effect on return intention. Zhang et al. [12] find that social and emotional values play equal roles in the decision to revisit a sharing website.

Although these articles identify high-level constructs such as social and economic benefits that affect the satisfaction and intention to use the sharing platform, more theoretical elaboration of these factors is necessary to better understand their underlying mechanisms. For example, cost savings alone are not enough to measure economic benefits, and risks are important but not adequately investigated in the

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[1] https://pando.com/2013/03/16/what-can-be-learned-when-sharing-leads-to-failing/
[2] https://techcrunch.com/2015/07/31/why-homejoy-failed-and-the-future-of-the-on-demand-economy/

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existing literature. Ron Williams, the founder of SnapGoods, using electric drills as an example, points out that although renting a drill on the platform has the benefit of avoiding item storage while saving half of the purchase price [13], the extra time and costs involved in picking up and returning the drill may be an obstacle. Thus, transaction costs and other concerns not adequately investigated in extant literature may affect user willingness to adopt the platform. Although recent studies of Henten and Windekilde [6], Munger [14], and Akbar and Tracogna [15] have examined the phenomenon of the sharing economy from the perspective of transaction cost, they focus mainly on cases such as Airbnb or Uber from an organizational perspective by conducting qualitative analyses or case discussions without empirical analysis. In order to better understand how users perceive different sharing products, it is crucial to build theoretical models and conduct empirical studies to investigate the effect of different factors that influence an individual's choice on the new channel when acquiring a particular product or service.

Toward this end, this study proposes a research model that extends the value-based adoption model (VAM) [16] from the consumer perspective to include both perceived benefits and transaction costs from transactional cost theory (TCT) [17]. The model provides a reasonable perspective for interpreting consumer choices on a sharing platform and is validated with an empirical study. The findings significantly extend our understanding of the role of transaction costs and different types of benefits on perceived value and intention to use a sharing platform. The remainder of this paper proceeds as follows. Literature and relevant theories are examined in the next section, followed by our research model and hypotheses. Research methodologies and findings are then reported. We discuss the findings and conclude in the final section.

2. Theoretical development

2.1. Research on the sharing economy

Sharing objects among neighbors is a common practice. The idea of the "sharing economy" (or "collaborative consumption") was initially introduced by Felson and Spaeth [18] who proposed a model in which a group of people share goods and services. In contrast to traditional commercial consumption, the cost of purchasing a good or service is divided across a group [6]. However, it was not until the widespread acceptance of the Internet that the sharing economy developed extensively [19]. Belk [20] further defines the sharing economy as people coordinating the acquisition and distribution of a resource for a fee or other compensation, such as bartering, trading, and swapping. With the improved efficiency of information exchange, users find collaborative consumption activities more convenient through online platforms [2,3]. People are no longer limited to their traditional network (e.g., neighborhood and rental stores) when sharing resources in online communities. In addition, the popularity of mobile devices also makes it easier to access traditional services [2,3]. Taking Uber, for example, the rise of mobile devices has allowed car drivers to flexibly offer services and consumers to easily find vehicles via this platform. The Internet has provided a significant improvement over the traditional rent business [21,22]. Trading through sharing platforms can significantly reduce transaction costs as compared to traditional models [6].

Research on the sharing economy proceeds along a few streams. First, researchers have examined it from the perspective of economic welfare. On the economic side, Lisa Gansky in *The Mesh* [23] shows how the new venture changes the current economic system in pursuit of better supply chain value distribution. The sharing economy stimulates economic benefits through the large-scale utilization of economic surplus [24]. Physical sharing and idle-time-based sharing are two main kinds of economic surplus at the individual level [24].

Another stream of research focuses on its impact on the general preference toward ownership [3,11]. In traditional transactions, consumers emphasize the ownership transfer of physical products; however, in the object sharing model the transaction is changed from ownership transfer to temporary access provision [25]. Through sharing, exchange, and leasing, transactions are made without the complication of changing ownership [2,19]. Customers use the object without spending a larger amount of money to own it. It is also possible to dispense with the responsibility for long-term storage and maintenance of owned items [2]. Compared to changing the long-term ownership of an item, the right to use an item is much simpler and has become favored by many users in recent years [26]. However, although sharing economy platforms change people's preference toward ownership, potentially challenging traditional models, the new job opportunities generated by sharing platforms also carry positive effects on incumbent firms. Go et al. [27] find that although the adoption of a ride-hailing sharing platform positively impacts new car sales in the short run, the long-term benefits remain unclear to the auto industry. Guo et al. [28] discover that car sharing disincentivizes passenger purchases of new cars by promoting more flexible travel solutions, but platform competition boosts new car demand and changes the impact on incumbent firms.

While the preference toward ownership has changed, the sharing economy also changes rental business from long-standing short-term services (such as traditional hotels or car rental companies) to the contemporary widely accessible services on sharing platforms [22]. Although traditional rental businesses have existed for many decades, the sharing economy has begun to flourish in the field only in recent years, creating a new kind of rental market [29,30]. As entrepreneurs take advantage of the Internet and technological advances to diminish information asymmetry, the sharing platform is an coordinating interface between two private parties as opposed to the traditional rental business in which the firm itself owns the service it provides to individuals [22,29].

Along with many studies that attempt to distinguish sharing economy platforms from traditional marketplaces, researchers have investigated innovative ways to help businesses to engage in the sharing economy [31,32]. Constantious et al. [31] find that organizational and market mechanisms are key to coordinating platform participation and creating competitive value. Four sharing economy models—"Franchiser", "Principal", "Chaperone", and "Gardener"—are proposed to help businesses to realize their value proposition and strategic intent while exploiting the growing fluidity of organizational boundaries [31]. Zuo et al. [18] develop a model of service optimization and propose a data-driven approach to improving online car-hailing service quality in the sharing economy.

The last stream investigates the reason behind adoption of the sharing service. Mohlmann [10] conducts two studies to identify determinants that influence consumers' continual use of sharing services. User self-benefit such as utility, trust, cost savings, and familiarity are found to be determinants. Hamari et al. [11] find that people are motivated by the sustainability of sharing platforms, their enjoyment of the activity, and economic gains. They indicate out that sustainability is associated with participation in sharing platforms only when those with strong ecological consumption beliefs have positive attitudes toward the platform. Tussyadiah [3] adopts SET to examine factors that influence user satisfaction and future intention to use the platform in the context of peer-to-peer trip accommodations. Enjoyment, cost-saving, and amenities affect user satisfaction. Fagerstrom et al. [33] find that a seller's facial image and their expression together with prices and customer ratings influence buyer behavior. A negative facial expression or the lack of a facial image evokes avoidance tendencies to explore Airbnb's web page and decreases the likelihood to rent. From a relational benefits perspective, Yang et al. [34] demonstrate that confidence, social benefits, and safety benefits significantly affect commitment in sharing economy services which in turn influence customer loyalty. Davidson, Habibi, and Laroche [35] show that materialism plays an important role in sharing economy participation across

different cultures.

Prior research adopts a few theories. Mao and Lyu [36] synthesize the theory of planned behavior (TPB) [37] and prospect theory (PT) to examine the psychological factors that motivate people to reuse Airbnb. Attitude and subject norms are found to be significant determinants of repurchase intention; however, perceived behavioral control is not. Unique experience expectation, familiarity, and electronic word of mouth have both direct and indirect influences on repurchase intention, whereas perceived value and risk have direct impacts only on attitude, which indirectly affects repurchase intention. French, Luo, and Bose [38] integrate theoretical underpinnings including TPB, social capital theory (SCT), and SDT to identify motivations for participation. Social capital and trust contribute to the continual use of social tourism, which is becoming a powerful complementary mechanism for travel services. Liang et al. [39] propose a theoretical framework to examine satisfaction with Airbnb from the perspective of trust and processes of transaction and experience. Transaction-based satisfaction is found to be more important, and trust is the key factor to mediate its relationship with repurchase intention. Zhang et al. [12] examine the customer value proposition for the sharing economy. Among four customer values (i.e., social, emotional, technical, and economic), social and emotional values are found to be equally important in motivating customers to return to the sharing platform.

Table 1 summarizes the relevant empirical studies on sharing platforms and the identified factors behind the intention to use and satisfaction with the sharing platform. These studies primarily focus on selected determinants from single theories. Popular theories include attitude change theories such as the technology acceptance model (TAM) and TPB applied to assess technology users in an organizational setting for work purposes [16]. However, most of these studies model the issue from a behavior perspective. In addition to those behavioral factors, a more important perspective that is not yet thoroughly studied is the economic perspective of using a sharing platform. Consumers use a sharing platform for economic gains (e.g., lower price) and noneconomic benefits (e.g., convenience). To bridge this gap, in this study we adopt VAM [16] which we develop to capture personal adoption of the sharing platform based on the rational choice theory, that is, consumer choice based on a favored comparison between benefits and costs.

Although a consumer's perceived value of a product/services is not limited to functional aspects, in this study we focus on the required effort during the transaction process and the perceived benefits of the decision. This study explores the perceived benefits based on cognitive evaluation theory (CET) [40] and the required effort during the transaction process based on TCT [17] to validate the proposed model with empirical data. By a hybrid lens combining multiple theories, this study provides a profound view of the sharing economy in the real world.

2.2. Value-based adoption model

Although behavioral intention models (such as the TAM and theory of reasoned action (TRA) families) dominate technology adoption research in information systems, economic benefits are always a strong incentive for human behavior. An intuition for adopting ICT is that technology can bring value to the user (termed *perceived usefulness* in the TAM family). Instead of examining the issue from a behavioral perspective, VAM emphasizes the adoption intentions of individual

Table 1
Empirical studies on the sharing economy.

Study	Theory	Constructs		Major findings
Mohlmann [10]	None	• Cost savings • Familiarity • Trust • Utility • Satisfaction • Trend affinity	•Environmental impact •Community belonging •Smartphone capability •Likelihood of choosing a sharing option again •Internet capability •Service quality	Utility, trust, cost savings, and familiarity are important considerations for participation in B2C and C2C models. Service quality and community belonging are identified in B2C only.
Hamari et al. [11]	SDT	•Sustainability •Enjoyment •Reputation	•Economic benefits •Attitude •Behavioral intention	Sustainability, enjoyment of the activity, and economic gains are primary motives for participation in the sharing economy.
Tussyadiah [3]	SET	•Social benefits •Enjoyment •Economic benefits	•Sustainability •Amenities •Locational benefits	Enjoyment, cost savings, and amenities constantly affect satisfaction.
Fagerstrom et al. [33]	None	•Facial expressions •Price	•Customer ratings •Tendency to explore the web page	Facial expressions, price, and customer ratings influence consumers using Airbnb.
Yang et al. [34]	Relational benefits	•Confidence benefits •Social benefits •Safety benefits	•Special treatment benefits •Commitment •Customer loyalty	Confidence, social benefits, and safety benefits have positive effects on commitment in sharing-economy services.
Mao and Lyu [36]	TPB PT TPB	•Unique experience expectation •Perceived value •Perceived risk •eWOM •Economic value	•Familiarity •Attitude •Subjective norms •Perceived behavior control •Repurchase intention •Satisfaction	Attitude and subject norms are significant determinants of intention to repurchase, but perceived behavior control is not.
French, Luo, and Bose [38]	SCT SDT	•Networking value •Attitude •Trust	•Continued use intention •Bridging social capital •Bounding social capital	Social capital, trust, attitude, and satisfaction are factors that influence continued use intention in social networking tourism.
Davidson, Habibi, and Laroche [35]	None	•Materialism •Perceived utility	•Transformation expectations •Willingness to participate	Materialism leads to greater participation in the sharing economy.
Liang et al. [39]	None	•Transaction-based satisfaction •Experience-based satisfaction	•Institution-based trust •Disposition to trust •Switching intention •Repurchase intention	Transaction-based satisfaction has a positive effect on experience-based satisfaction. Trust is determined to mediate transaction-based satisfaction and repurchase intention.
Zhang et al. [12]	Customer value proposition	•Technical value •Economic value •Social value	• Emotional value • Repurchase intention	Social and emotional values play equal roles in revisiting a sharing website.

users with focuses on the rational choice of value maximization [16,41]. Although various value typologies have been proposed [42,43], the concept of perceived value of VAM follows Zeithaml [44] who defines the perceived value as the result of a user evaluating the effectiveness of a product or service, comprehensively considering what he or she needs to pay and what he or she can gain, resulting in an overall assessed value of the product or service. In short, this study also defines perceived value as a consumer's evaluation between the perceived benefits and perceived costs (sacrifice). That is, the perceived value is the net gains from the increase in perceived benefits and the reduction in perceived cost.

2.2.1. Perceived benefit

The perceived benefits obtained from a transaction are what motivate people to take actions such as using a sharing platform. These benefits can be intrinsic and/or extrinsic. Deci [40] proposes the CET, which states that motives are influenced by internal and external factors. Intrinsic motivation is defined as "when the user completes something, the motivation for the matter may increase due to personal interest or spiritual satisfaction." External motivation is defined as that, when something is achieved, the user may gain substantial benefits which thus strengthen the motivation. Consumers assess their time spent and effort [44], potential economic benefits [45], and external rewards [11] to weigh the perceived value in adopting a technology.

A major incentive for adopting a sharing platform is to offer better economic solutions. Price flexibility is an example. Airbnb provides accommodation alternatives priced at different levels for users to choose from [1]. In addition to monetary benefits, the sharing economy provides relational and other benefits. Henten and Windekilde [6] find that most users come from volunteering to help others or hope to gain social experiences made by sharing traditional objects. Kim, Yoon, and Zo [46] find that the sharing economy provides more opportunities to establish or maintain long-term relationships with others. For instance, consumers of Airbnb can interact with landlords from different backgrounds and in different countries for a unique experience that is not available from traditional restaurant or hotel booking services [1]. These allow consumers to satisfy their curiosity and pursue unique experiences with products not for long-term usage [47]. Value-based theory argues that consumer intention for transactions on a sharing platform is driven by the aggregated assessment of perceived benefits and perceived costs.

2.2.2. Perceived costs

Perceived costs are what consumers think they are paying to complete a transaction. It is the sacrifice of consumers that negatively affects their perceived value in a transaction [48]. Zeithaml [44] proposes that the sacrifices made by consumers in a transaction are not limited to the direct price of the transaction but also include other factors required to successfully complete the transaction such as time, search, and convenience costs. Such less tangible parts of the final cost are generally considered part of the entire transaction cost. The literature has found that the factor of transaction costs is a major factor that drives the use of the Internet for e-commerce (e.g., [16,41,49]). In addition to value addition, transaction costs involved in object sharing are also a potential factor that affects platform adoption. Hence, we use this as a surrogate for the sacrifice dimension of value-based theory, as described below.

2.3. Transaction cost theory

The concept of transaction costs was initially proposed by Coase [17]. Williamson [50] classifies transaction costs into ex ante costs and ex post costs. Ex ante costs include information collection, contract negotiation, and contracting costs. Ex post costs, however, contain contract supervision costs. The adoption of transaction costs in e-commerce research has a long history. Liang and Huang [51] adopt TCT to interpret why certain products are easier to sell in online stores. Teo and Yu [52] classify transaction costs involved in online transactions into searching costs, monitoring costs, and adapting costs. The searching cost is that associated with the time or effort expended by consumers in finding useful content associated with products or services and selecting proper vendors. Monitoring costs are costs spent by consumers to ensure that contracts are faithfully executed. Adapting cost is the cost consumers bear to deal with exceptions during contract implementation or costs associated with after-sales services. Along with the online transaction process, consumers complete activities such as searching for information, and monitoring the on-going process to ensure a favorable deal. Hence, reducing transaction costs can be a motivation for consumers to explore using a sharing platform. The literature has identified major factors that may affect transaction costs such as uncertainty and asset specificity (e.g. [53,54],).

(1) Uncertainty

Humans have limited processing power in short-term memory leading to decision biases under uncertainty [55], which increases the need for and the cost of gathering and processing more information. Wu et al. [56] demonstrate that uncertainty in an online shopping environment significantly increases the information searching cost leading to weak repurchase intention. Liang and Huang [51] suggest that online transactions are affected by two types of uncertainties: (1) product uncertainty, in which goods or services may not meet the customer's expectations, and (2) process uncertainty, in which the customer is unsure whether the overall transaction process is trustworthy. In other words, the customer may not be comfortable with the transaction because of the uncertainty associated with the target product or the transactional process. Higher uncertainty may lead to a lack of confidence in the trading environment and increase customers' perceived transaction costs. For a sharing platform, these uncertainties may be elaborated as the follows:

a Product uncertainty: Consumers must assess whether the product or service on the sharing platform meets their expectations and whether the product is as claimed. For example, when using car sharing services such as Uber, the consumer may be unsure of the quality of the engaged driver and the car. This is why sharing platforms often attempt to provide as much information as possible. Uber uses consumer ratings and vehicle information to reduce concern about the driver and the car.
b Process uncertainty: Consumers lack adequate information assuring that the whole transaction process will be completed as expected. In car sharing services, for instance, potential process uncertainties include whether transactions are properly handled, so that the driver will pick up the order, arrive on time, drive carefully to the destination, and whether the correct amount of money will be charged.

(2) Asset specificity

Another key factor in transaction costs is asset specificity. Asset specificity, or specific asset investment (SAI), is investing in specific assets in order to maintain an ongoing relationship with a particular seller and whose deployment incurs substantial switching costs [54,57]. Several types of asset specificities have been reported: location, human asset, physical asset, dedicated asset, time, and brand (e.g., [58–60]).

Previous studies on asset specificity are mixed. For example, Bolton et al. [61] find that asset specificity does not affect the members of loyalty programs while investigating consumer adoption of a credit card service. Similarly, Kivetz and Simonson [62] discover that while some loyalty programs are highly successful (e.g., frequent flier programs), some fail (e.g., Internet network loyalty programs). They show that the effect of asset specificity on perceived value depends on whether consumers believe that loyalty programs offer an idiosyncratic fit for them. However, Kivetz [63] claims that asset specificity is likely to stir up consumer resistance, thus decreasing their perceived value. Chiou et al.

[64] argue that online shoppers are more likely to consider asset specificity to be an increased transaction cost. Che et al. [65] demonstrate that asset specificity in terms of personalization and trust positively affects the rate at which consumers revisit an online group-buying website. Hence, findings about asset specificity on transaction costs and consumer value are inconclusive.

In summary, when the sharing platform is convenient and accessible, users can easily break the limitations of time and space to share their objects and time. Information technology can reduce transaction costs by decreasing uncertainty. The large number of providers also reduces asset specificity associated with transactional location and time. Hence, to investigate why certain sharing platforms succeed while others fail, the factors of uncertainty and asset specificity should be accounted for. For example, vehicle availability as depicted on the map of the Uber App and credit card payment significantly reduces the uncertainty when the user intends to use the Uber service. The high density of Uber drivers also minimizes customer waiting time and widens the area where service is convenient. Hence, in building our research model, it is useful to combine TCT with VAM.

3. Research model and hypotheses

As described in the previous section, the VAM and TCT theories are useful for studying the relationship between factors and the intention to adopt sharing platforms from an economic perspective. Here the intention follows the definition of behavior intention proposed by Wakefield and Barnes [66]: the degree of intention to use products or services in the future. If a platform can enhance the perceived value, consumers have a higher intention to adopt the platform. This is supported by previous studies in information systems. For instance, Wu et al. [56] claim that online repurchase intention has a positive relationship with users' perceived value. Roostika [41] also mentions that perceived value is an important factor influencing user participation. Perceived value derived from perceived gains and losses during a transaction process affects consumer intention with respect to a product or service [67]. Therefore, in this study, we conceptualize perceived value from Zeithaml [44] and define it as an assessment of the value of a product or service based on the combined effects of increased benefits and reduced sacrifices (cost). The following hypothesis is posited.

H1. Consumers' **perceived value** of a sharing platform positively influences their **intention** to adopt it.

This hypothesis can be further extended with the VAM and TCT described in the previous section to develop a comprehensive research model, as shown in Fig. 1. The remaining six hypotheses are elaborated below.

From the cost perspective, price (monetary spending) is not the sole consideration; other intangible costs (nonmonetary costs) must also be considered. Zeithaml [44] suggests that reducing consumers' sacrifice can increase their perceived value for the product, for instance, ready-to-serve foodservice and home delivery. If consumers can easily find and comprehend the information, their time and effort can be saved, leading to a higher perceived value. In using a sharing platform, transaction costs better reflect the effort required for consumers to make a choice that might impede them from engaging in relational exchanges [56]. We, therefore, include the transaction costs as a major cost arising from searching, monitoring, and adapting a product or service while evaluating uncertainty and asset specificity in the sharing platform. Thus, we posit Hypothesis 2 (H2) below:

H2. **Transaction costs** from a sharing platform are negatively associated with the consumer's **perceived value**.

In terms of the perceived benefits, both economic and noneconomic benefits can affect the perceived value of a sharing platform. The literature shows that the perceived monetary benefits directly influence the perceived value [48,68]. In addition to monetary savings, other internal and external rewards derive from Internet accessibility, service diversity, and the ability for socialization [3]. For example, Kim et al. [25] observe that a sharing platform allows users to obtain social value (social benefit) since they have more opportunities to expand their network of interactions with others. Furthermore, users may perceive "epistemic benefit", which satisfy the user's curiosity and concern the novelty of new products and new experiences. Hence, in this study we define economic benefits as focusing on monetary and time benefits and noneconomic benefits as including social benefits and epistemic benefits. Hence, we posit H3 and H4 below.

H3. The perceived **economic benefits** positively affect the consumer's **perceived value** of the sharing platform.

H4. The perceived **noneconomic benefits** positively affect the consumer's **perceived value** of the sharing platform.

When using a sharing platform, uncertainty and asset specificity are the main factors that affect the transaction costs. Uncertainty reflects the cost associated with unexpected outcome and information asymmetry. Bhatnagar et al. [69] demonstrate that for online shoppers, reducing the perceived unpredictability in the shopping environment is more important than convenience. As the sharing economy is an emerging marketplace, customers may be uncertain about the overall trading environment, especially in comparison with traditional transactions. For a better understanding of the online service exchange, consumers must spend time and effort to evaluate the necessary product/service information. Such information searching processes increase the uncertainty associated with online transactions, leading to increased transaction costs [56]. This study extends the uncertainties from Liang and Huang [51] and further defines the construct of "uncertainty" as a cost associated with product uncertainty and process uncertainty. We therefore hypothesize:

H5. **Transaction cost** is positively affected by the consumer's perceived **uncertainty**.

Asset specificity refers to the extent to which the investment was made in support of a transaction with substantial switching costs [54,57]. In the sharing platform, it is defined as an investment with its associated location, human asset, physical asset, dedicated asset, time, and brand (see Appendix C). As the social economy has emerged in recent years, it can be seen as a whole new transaction type for customers. Devaraj et al. [70] find that asset specificity is associated with the features of online websites. When the sharing platform provides more convenient and available access, people are no longer locked to their immediate network since they can easily break the limitations of time and space to share their properties. Hence, we posit hypothesis H6:

H6. The **transaction cost** of a sharing platform is negatively affected by the consumer's perceived **asset specificity**.

The sharing platform is an alternative to traditional channels; via such digital platforms, a wide variety of products or services can be provided. The different attributes of products or services affect transaction costs in various ways. For example, as products shared on Uber and Airbnb are very different, they are likely to have different effects on transaction costs and perceived value. Different customers may have different levels of acceptance for different products/services. According to Ma et al. [24], products available for sharing include physical products (e.g., rooms and hammers) and intangible services (e.g., time sharing). We hereby hypothesize H7 below.

H7. **Product type** is the moderator between **transaction** cost and **perceived value**.

4. Research methodology

To test the proposed research model, a web-based quasi-experiment was conducted to solicit user responses. This is appropriate as most

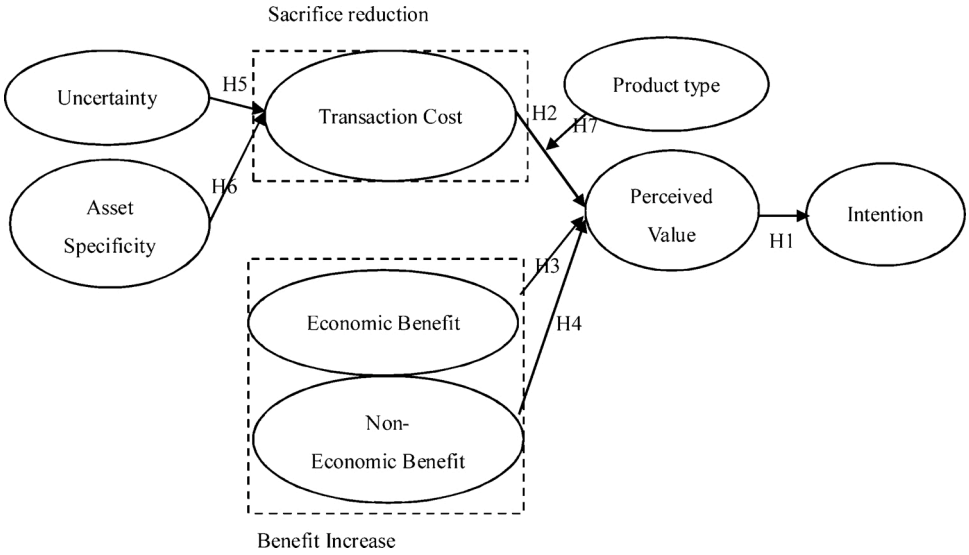

Fig. 1. Research model.

sharing platforms are operated online and consumers use their services online. Web-based experiments allow data to be collected from a diverse sample that is close to the real-world users of most sharing platforms [71]. This section describes our experimental design and measurements.

4.1. Experimental tasks and measurement

The experiment included controlled scenarios presented to the subject as well as the collection of their feedback via questionnaires. In designing the scenarios, we considered the nature of products or services to be shared, as differences therein affect the perceived value and intention to use. We chose two types of sharing objects: tangible products such as hammers or rooms, and intangible objects such as time sharing [24]. For greater variety, in this study we chose five different sharing objects (see Table 2), three physical products, and two time-sharing services at different price levels. Details are provided in Appendix A. To ensure that users were not influenced by previous experience with existing sharing platforms and to control the self-selection bias of the samples, we built an experimental website and randomly assigned the five sharing scenarios to participants.

The questionnaire was designed based on the literature [3,16,51,52,72]. All measures of the constructs refer to existing prominent published sources. We adapted previously validated measures according to the procedure in Moore and Benbasat [73]. In total, there were 36 measurement items in the questionnaire. Appendix B shows the construct details and measurement items. Subjects responded on a 5-point Likert scale with 1 as "strongly disagree" and 5 as "strongly agree". To ensure content validity, a thorough review of the relevant literature was first conducted [74] and the instrument items reviewed by a panel of experts including two professors and one graduate student majoring in information systems.

Table 2
Sharing objects.

Product type	Characteristic	Scenario
Physical Product	High price (People cannot easily own)	Room
	Median price (Easier to own compared to higher price item)	Parking space
	Low price (Can easily own)	Clothes
Idle time	Professional service (High skill)	Chef sharing
	Labor service (Low skill)	Cleaning

4.2. Data collection

As most sharing platforms are available online, all participants were recruited online. We recruited participants from the PTT Bulletin Board System (a Taiwanese social community)[3] and Facebook. Interested participants followed the link we provided in the posts to access the experimental website, and a lucky draw to receive a monetary reward (about $3) was given. To eliminate multiple access, we issued a demographic questionnaire to collect participants' basic information at the beginning of the experiment. A pilot study included 160 observations (around 30+ for each scenario). The results of which show the quality of the experimental design and measurements to be acceptable; as such, no major changes were then made to the instrument.

In the formal experiment, 486 responses were received. After excluding 10 invalid observations, 476 were valid for data analysis. Table 3 shows the demographic information of the participants. The gender of the participants was 30 % female and 70 % male. The largest age group was 21–30, which accounts for 64.7 % of the sample. The majority education level was undergraduate, accounting for 56.1 % of the total, followed by graduates, with 37.4 % of the sample. The respondents' main occupation was student (34.9 %), followed by those working in the information industry (18.2 %). Among the participants, 43.3 % had used previously sharing platforms.

5. Data analysis and results

Since this research design includes both reflective and formative constructs, partial least squares (PLS) was chosen for data analysis because of its ability to analyze both reflective and formative models [75]. SmartPLS 3.0 [76] was used. Since 60 % of subjects were aged from 21 to 30 and 70 % were male, we set age and gender as control variables in the analysis model to ensure that their effects were contained.

5.1. Data reliability and validity

To ensure data quality, Harman's single factor test was applied to

[3] PTT was founded in 1995 and is the most popular discussion board in Taiwan. It has more than 1.5 million registered users and 200,000 discussion boards on various topics. https://en.wikipedia.org/wiki/PTT_Bulletin_Board_System

Table 3
Demographic information.

		N	%			N	%
Gender	Female	143	30.1%	Education level	< High School	31	6.5%
	Male	333	69.9%		Undergraduate	267	56.1 %
Age	< 20	37	7.8%		Graduate	178	37.4 %
	21–30	308	64.7 %	Occupation	Catering	9	1.9%
	31–40	80	16.8%		Clothing	10	2.1%
	41–50	25	5.3%		Finance	28	5.9%
	51–60	22	4.6%		Information	87	18.2 %
	> 60	4	0.8%		Manufacturing	27	5.7%
Monthly disposable income	< NT$10000	178	37.4 %		Medical/Biotechnology	12	2.5%
	NT$10001–20000	90	18.9%		Military /Civil servant/ Education	35	7.4%
	NT$20001–30000	59	12.4%		Service	43	9%
	NT$30001–40000	49	10.3%		Student	166	34.9 %
	NT$40001–50000	39	8.2%		Other	59	12.4%
	> NT$50000	61	12.8%				
Experience with sharing platform					Yes	206	43.3 %
					No	270	56.7%

check whether common method variation (CMV) was a problem in the study [77]. The largest factor in this study explains 30 % of the variance, and multiple factors are extracted. Hence, CMV is not a concern for further analysis.

We use Cronbach's alpha to check data reliability. As shown in Table 4, all values exceeded the commonly accepted value of 0.7, which indicates acceptable data reliability. To check our construct validity, we calculate the average variance extracted (AVE) of each construct. Also shown in Table 4 are all 28 reflective items' loadings that exceed the hurdle value of 0.5. The composite reliability (CR) values range from 0.844 to 0.957.

In terms of the formative items of asset specificity, we examined their weights and *t*-statistics of the latent variables to determine whether the constituent indicators are appropriate. The result is shown in Table 5. Six items—SPE2, SPE3, SPE4, SPE5, SPE6, and SPE8—do not attain a significance level of $p < 0.05$, indicating low influence. Therefore, asset specificity is better measured by using two dimensions: location specificity and brand specificity. According to Hair's process of formative testing [78], we keep all items considering their effect on content validity.

The common test of discriminant validity is based on whether the square root of the AVE for all constructs is greater than the correlation coefficient between constructs [79]. The square root of the AVE exceeds the correlation between the two respective constructs for all construct pairs, showing the presence of discriminant validity (Table 6).

Table 4
Confirmatory factor analysis for measurement model.

Construct	Measurement item	Loading	AVE	CR	Cronbach's alpha
Product uncertainty	UNC1	0.676	0.646	0.844	0.723
	UNC2	0.888			
	UNC3	0.832			
Process uncertainty	UNC4	0.912	0.841	0.914	0.811
	UNC5	0.922			
Searching cost	TCS1	0.909	0.828	0.906	0.792
	TCS2	0.910			
Monitoring cost	TCS3	0.884	0.776	0.874	0.711
	TCS4	0.878			
Adapting cost	TCS5	0.838	0.747	0.899	0.831
	TCS6	0.871			
	TCS7	0.884			
Economic	EBF1	0.724	0.610	0.862	0.787
	EBF2	0.747			
	EBF3	0.836			
	EBF4	0.811			
Social benefit	NBF1	0.820	0.679	0.863	0.762
	NBF2	0.770			
	NBF3	0.878			
Epistemic benefit	NBF4	0.896	0.823	0.903	0.786
	NBF5	0.918			
Perceived value	PEV1	0.865	0.757	0.926	0.893
	PEV2	0.855			
	PEV3	0.900			
	PEV4	0.861			
Intention	PAR1	0.934	0.880	0.957	0.932
	PAR2	0.936			
	PAR3	0.944			
Uncertainty (Second order)	Product uncertainty	0.517	–	–	–
	Process uncertainty	0.607	–	–	–
Transaction cost (Second order)	Searching cost	0.432	–	–	–
	Monitoring cost	0.383	–	–	–
	Adapting cost	0.346	–	–	–
Noneconomic benefit (Second order)	Social benefit	0.598	–	–	–
	Epistemic benefit	0.587	–	–	–

5.2. Structural model

SmartPLS 3.0 [76] provides the standardized root mean square residual (SRMR, a value between 0–1; the closer to 0, the more perfectly matched) to evaluate the fitness of the research model. The saturated model of SRMR assumes that the number of paths in the structural model is the same as the correlation between the constructs in the measurement model; the estimated model is calculated based on the sample dataset itself and rows. According to scholars' suggestions [80–82], when the SRMR of the saturated model and estimated model is less than 0.08, the model fit is good [80], if the two are less than 0.1, the model fit is acceptable [81], and the smaller the gap between the two values, the better the model is [82]. The SRMR value of our saturated model is 0.091, and the SRMR value of the estimated model is 0.095. Both are

Table 5
Potential variables of asset specificity construct.

Latent variable	Measurement item	Outer weights	*t*-value
Asset specificity (second order)	SPE1 (location specificity)	0.578	4.226***
	SPE2 (human asset specificity)	−0.201	1.092
	SPE3 (human asset specificity)	0.229	1.263
	SPE4 (physical asset specificity)	−0.248	1.248
	SPE5 (dedicated asset specificity)	0.004	0.020
	SPE6 (time specificity)	0.134	0.936
	SPE7 (brand specificity)	0.471	3.029**
	SPE8 (brand specificity)	0.234	1.5896

Table 6
Discriminant validity and correlation coefficient matrix.

Construct	1.	2	3	4	5	6	7	8	9	10
1. Product uncertainty	0.804									
2. Process uncertainty	0.58	0.917								
3. Searching cost	−0.134	−0.319	0.91							
4. Monitor cost	−0.203	−0.308	0.661	0.881						
5. Adapting cost	−0.125	−0.235	0.539	0.636	0.864					
6. Economic	−0.12	−0.305	0.717	0.641	0.561	0.781				
7. Social benefit	−0.097	−0.043	0.303	0.352	0.341	0.37	0.824			
8. Epistemic benefit	−0.051	−0.125	0.348	0.322	0.361	0.364	0.425	0.907		
9. Perceived value	−0.199	−0.305	0.633	0.579	0.519	0.719	0.465	0.45	0.87	
10. Intention	−0.254	−0.324	0.59	0.552	0.485	0.633	0.413	0.372	0.731	0.938

within the acceptable range (below 0.1), and their difference is very small. It meets the standards recommended by Wang and Wang [81] and Henseler et al. [82], so the model fit is acceptable.

The result is shown in Fig. 2. The R-square values of the proposed model range between 0.196 (transaction cost) and 0.604 (perceived value). Hypothesis H1 is supported: perceived value has a positive effect on participation intention ($\beta = 0.727$, $p < 0.001$). This means that the higher the user's perceived value of a product or service, the higher the user's intention to use the sharing platform. Hypothesis H2 is also supported. Transaction costs are found to negatively affect the perceived value (β = -0.233, $p < 0.001$), indicating that the higher the transaction costs perceived by the user, the lower the perceived value of the user. Hypotheses H3 and H4 are supported. The economic benefits ($\beta = 0.438$, $p < 0.001$) and noneconomic benefits (β=0.243, $p < 0.001$) have positive effects on the perceived value. Uncertainty has a positive effect on transaction cost ($\beta = 0.306$, $p < 0.001$), but asset specificity has a negative effect on transaction cost (β = -0.329, $p < 0.001$). Hypotheses H5 and H6 are supported.

5.3. Moderation analysis

To further understand the effects of different sharing objects, we analyzed the moderation effect. A multigroup PLS analysis [83,84] was conducted to compare differences between physical products and time-based services. The sizes of these subgroups were 251 and 225, respectively, which exceeds the suggested sample size of 200 for a reasonable statistical analysis [85]. Table 7 shows the result of the two-group analysis. Most hypotheses are supported for both physical products and time-based services. However, the effect of asset specificity on transaction cost is not statistically significant for physical products.

Table 7
Differences between two types of sharing objects.

	Physical products		Time-based services		*t*-value
	Path coefficient	Std dev.	Path coefficient	Std dev.	
Perceived value -> Intention	0.716***	0.036	0.738***	0.04	−0.411
Transaction costs -> Perceived value	−0.282***	0.062	−0.189**	0.074	0.971
Economic benefit-> Perceived value	0.431***	0.071	0.442***	0.072	−0.109
Noneconomic benefit -> Perceived value	0.181***	0.048	0.307***	0.075	−1.445△
Uncertainty -> Transaction costs	0.345***	0.055	0.233***	0.061	−1.370△
Asset specificity -> Transaction costs	−0.306	0.224	−0.403***	0.06	−0.401

*** Significant at 1% level.
** Significant at 5% level.
△ Significant at 10 % level.

Further checking the constituent indicators of asset specificity for two groups (see Table 8) shows that location specificity has the highest effect size but is close to a marginal significance on a one-tailed *t*-test for physical products, whereas human asset specificity and brand specificity are significant for time-based services. These are reasonable for our experimental scenarios, as the tangible sharing objects such as rooms and parking space are location-sensitive, while chef for cooking and cleaning services rely more on the quality of the person who provides the

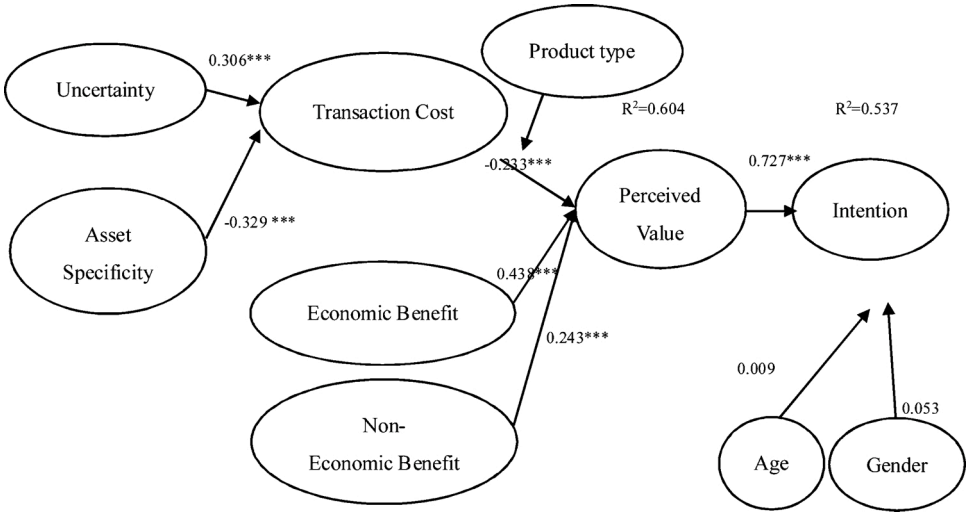

Fig. 2. Structural model.
Note: *** $p < 0.001$.

Table 8
Measurement effect of asset specificity.

Latent variable	Measurement item	Physical products		Time-based services	
		Outer weights	*t*-value	Outer weights	*t*-value
Asset specificity	SPE1 (location specificity)	0.778	1.589△	0.320	1.833△
	SPE2 (human asset specificity)	−0.066	0.262	−0.103	0.482
	SPE3 (human asset specificity)	−0.357	0.979	0.457	2.372*
	SPE4 (physical asset specificity)	−0.173	0.581	−0.212	1.021
	SPE5 (dedicated asset specificity)	0.206	0.741	−0.125	0.592
	SPE6 (time specificity)	0.120	0.670	0.014	0.082
	SPE7 (brand specificity)	0.368	1.281	0.511	2.550**
	SPE8 (brand specificity)	0.107	0.546	0.362	2.178*

service. A consumer may want to pay more to share a Michelin chef than he or she would pay for a lousy chef.

While most hypotheses were supported for different product types, the effect size of noneconomic benefits on perceived value and that of uncertainty on transaction costs are different at a marginally significant level of 0.1 (at one-tailed test). This indicates the possibility that noneconomic benefits carry more weight in sharing time-based services, while the uncertainty of transaction costs carries more weight in sharing physical products. This might imply that consumers perceived higher value of noneconomic benefits from time-based services on the sharing platform and perceived higher uncertainty when searching for physical products on the sharing platform which is consistent with previous research [52,56]. Although the *p*-value does not meet the significance level in the two-tailed test, using the one-tailed hurdle is reasonable as their effect sizes are in the same positive and negative direction. Their difference shows that one is larger or smaller than the other, which also makes sense. Hence, the result still yields insights into the phenomena.

6. Discussion and conclusion

6.1. Discussion

This study examines consumer intention to use a sharing platform from the economic perspective and proposes an extended value-based model that includes economic benefits, noneconomic benefits, and transaction costs as three major value drivers. Our empirical results indicate that the model has good interpretability, demonstrating the following major results:

(1) **Perceived value well predicts the intention to adopt a sharing platform.** Users with a higher perceived value of a sharing platform are more likely to adopt the sharing platform. The perceived value is based on the assessment of both sacrifice and benefits. The R-square value of 0.537 shows a good interpretation of variance. Furthermore, the findings of this study complement prior studies that use behavior-oriented adoption models such as TAM and unified theory of acceptance and use of technology (UTAUT). Hence, we demonstrate that for a sharing platform to succeed, the key is increasing the perceived value of its users.

(2) **Perceived value can be increased by reducing transaction costs and increasing the perceived benefits.** Our findings indicate that both increasing benefits and reducing transaction costs increase the perceived value of a sharing platform. Therefore, objects shared on the platform must increase benefits and/or reduce costs. We find that the perceived benefits have a greater influence than the perceived transaction costs. Both economic and noneconomic benefits matter. Given that most rational users are economically driven [44,56], this makes sense. However, the effect of certain factor on transaction costs, such as the potential risk of defective products or services on transaction cost, may be perceived differently by different users.

(3) **Transaction costs are positively associated with perceived uncertainty.** This indicates that sharing platforms may not work well when high uncertainty is associated with the object being shared or with the process for sharing the object. Higher uncertainty decreases user intention to take advantage of the convenience offered by a sharing platform which is consistent with previous research [52,56]. For instance, clothes sharing (e.g., Tulerie.com) tends to have higher uncertainty (due to various sizes, styles, shapes, and fitness) than cars in vehicle sharing (e.g., Avis and Uber). This may explain why Tulerie.com is much less popular than Uber.com.

(4) **Transactions costs are negatively associated with perceived asset specificity.** This means higher asset specificity tends to have a lesser effect on transaction costs. A sharing platform that provides products with high asset specificity is more likely to reduce the perceived transaction costs and increase the perceived value. For instance, room sharing has a higher asset specificity than hammer sharing. As sharing platforms provide more convenient and available access, the lock-in problem, in which consumers must rely on a certain provider, seems to be reduced in the sharing economy.

(5) **The effect of sharing platforms varies among different sharing targets.** The different attributes of the sharing target seem to explain why certain sharing platforms succeed while others fail. Our findings from the moderation analysis on two different types of sharing objects indicate that the effect of asset specificity is significant for time-sharing products but not for physical products. The only specificity that approaches statistical significance is the location. Although location has been identified as an important aspect of the sharing economy in several studies [86,87], there remains a paucity of research on the effect of location on transaction costs. Our study demonstrates that the effect of location on transaction costs is much greater for physical products than for time-based services. Economic benefits are a must for both types of products but noneconomic benefits have a greater impact on time-sharing services than on physical products. This may be because time-sharing services are more intangible and hence brand and human resources are more influential, which is evidenced by the significant effect of brand and human asset specificity shown in Table 8.

Overall, a sharing platform allows individuals to share their resources with others. A key to the success of a sharing platform is attracting enough users. In this study, we find that perceived value is a major factor affecting the intention to use a sharing service. This value is composed of economic and noneconomic benefits along with the reduction of transaction costs. The integration of VAM and TCT explains the intention to participate at a sufficiently high explaining power (R-square = 0.537). We also find that the effects of these factors depend on the nature of the sharing targets.

6.2. Implications and limitations

The implications of our findings are two-fold. First, we propose a model from the economics perspective for interpreting consumer adoption of sharing platforms, and empirically evaluate the explaining power of the model. This model complements many previous studies based on behavioral change models such as TAM. Second, perceived value is found empirically to be the main driver for consumer adoption of a sharing platform. The perceived value is affected by the increase of perceived benefits and the perceived reduction of transaction costs. This provides a new lens for studying technology adoption. Furthermore, our empirical findings show that success factors differ when the sharing objects vary. This also explains why many followers in the sharing economy fail when they choose a product without carefully reviewing the value drivers associated with the sharing object. These findings have significant theoretical and practical implications.

The main practical implication is that when a sharing platform is introduced, innovators must carefully assess whether the intended sharing object creates economic and social benefits, and reduces transaction costs. Unless the overall perceived value is positive, there is little chance of succeeding. In addition to economic benefits (such as lower price), managers must pay attention to noneconomic benefits and transaction costs, especially when the sharing object is not physical, where asset specificity and uncertainty play important roles in transaction costs.

The different trading mechanisms of a sharing platform may be prone to more uncertainty than the transactions in the traditional market. For example, the price and vehicle location information provided by Uber may reduce the uncertainty as compared with booking a taxi, which gives Uber competitive advantages. Providing more information about the product and transaction process can lower user uncertainty on platform trading. Among asset specificity concerns, location and brand have greater impacts on transaction costs and hence deserve greater attention.

Despite the significant contributions of this study, potential limitations exist. First, our findings are derived from data collected from an online experiment conducted in Taiwan[4] as an export-oriented developing economy with a high population density and ethnic diversity. Hence, readers need to be sensitive to cultural and economic differences when the results are applied to a significantly different economy, such as culturally different European countries or geographically different Russia. Second, consumers have different concerns when using sharing platforms that involve different objects. In the experiment, although five different sharing targets are included, these cannot represent all products or services available on the market. Attention must be paid to differences when the result is applied to sharing targets other than those in this study. While this study focuses on the consumer perspective that influences an individual's intention to use online platforms for sharing different objects, comparing two platforms that provide the same sharing objects could be an interesting future work. Third, this study focuses on the consumer but not the vendors who provide the products and services. Our findings are useful for attracting customers to use sharing platforms; we do not attempt to attract vendors such as Uber drivers. Findings may differ when the same model is applied to study product or service vendors of a sharing platform. Last but not least, while we have carefully executed the experiment, the findings are based on data collected from an online experiment, which may have certain inherent constraints. The sample size is relatively small when the actual user size is hundreds of millions, such as Uber and AirBnB. Hence, our results may deviate from actual decision-making in the real world due to self-selection bias or discrepancies between the experimental scenarios and reality. Indeed, this limitation is shared among all self-reported empirical studies widely used in investigating user intentions to adopt technology [16,88,89]. We have done our best to meet the statistical requirements for data analysis and the issue should not undermine the theoretical and practical contributions of this study.

Author statement

Ting-Peng Liang performed conceptualization, methodology, and supervision.

Yi-Ling Lin performed methodology, writing—original draft preparation, and writing—reviewing and editing.

Shiao-Chi Ho performed validation, formal analysis, and investigation.

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Appendix A. Task Scenarios

(1) Room

You plan to travel abroad and have an accommodation need. There is a sharing platform where you can easily find private room accommodations provided by individuals or institutions who are not commercial hotel operators. The sharing platform provides information including the price, layout, decoration photos, and consumer comments. You can view a list of rooms that meets your needs and complete the entire transaction through the platform. The platform charges a small commission fee for the transaction. If you need to book a room accommodation, would you use the sharing platform to find a room accommodation based on the information provided above.

(2) Parking space

You plan to drive somewhere and have a parking need. There is a sharing platform where you can easily find a private parking space provided by individuals or institutions that are not commercial parking services. The sharing platform provides information including its price, its location, and consumer comments. You can view a list of parking spaces that meets your needs and complete the entire booking and payment transaction through the platform. The platform charges a commission fee for the transaction. If you need for a parking space, would you use the sharing platform to find a parking space based on the information provided above.

(3) Clothes

You need different clothing styles such as a Halloween costume. There is a sharing platform where you can easily rent private clothes provided by individuals who are not commercial sellers. The sharing platform provides information including the price, size, and consumer comments. You can view a list of available clothes that meets your needs and complete the entire transaction through the platform. The platform charges a commission fee for the transaction. If you need to rent clothes for certain purposes, would you use the sharing platform to rent based on the information provided

[4] https://www.taiwan.gov.tw/content_8.php

above.

(4) Chef sharing

You need a good chef to host a formal dinner at home. There is a sharing platform where you can easily find a private chef who is good at cooking but not a commercial restaurant operator. The sharing platform provides information including his/her price, specialties, dishes' photos, and consumer comments. You can view a list of chefs that meets your needs and complete the entire booking and payment transaction through the platform. The platform charges a commission fee for the transaction. If you need such a private chef, would you use the sharing platform to find a chef based on the information provided above.

(5) Cleaning service

You need to hire someone to help clean your home. There is a sharing platform where you can easily find cleaners who are not from professional cleaning companies but good at cleaning houses such as housewives who have time. This sharing platform provides information including his/her expertise and background, the price of the service and his/her reputation from other customers. You can view a list of cleaners that meet your needs, and complete the entire appointment and payment transaction through the platform. The platform charges a commission fee for the transaction. If you need such cleaning help, would you use the sharing platform to find a cleaner based on the information provided above.

Appendix B. Questionnaire Items (The Room Cleaning Sample)

CONSTRUCT	ITEM	
	Please indicate the likelihood that you would adopt a sharing platform (Scale: (1) very low, (5) very high)	
Participation intention [52]	PAR1: The likelihood that I would use a sharing platform for home cleaning services is high.	
	PAR2: The probability that I would consider using a sharing platform for home cleaning services is high.	
	PAR3: My willingness to using a sharing platform for home cleaning services is high.	
Perceived value [16]	PEV1: Given the required fee, the use of a sharing platform for home cleaning services is valuable for me.	
	PEV2: Compared to the effort I would need to exert, the use of a sharing platform for home cleaning services is beneficial to me.	
	PEV3: Compared to the time I would need to spend, the use of a sharing platform for home cleaning services is worthwhile to me.	
	PEV4: Overall, the use of a sharing platform for home cleaning services delivers me good value.	
Economy benefit [3]	Monetary benefit	EBF1: The price of using a sharing platform for home cleaning services might be higher than traditional cleaning services.
		EBF2: An additional fee for using a sharing platform for home cleaning services might be needed.
		EBF3: Using a sharing platform for home cleaning services saves me money.
		EBF4: Using a sharing platform for home cleaning services benefits me financially.
	Time benefit	EBF5: Using a sharing platform for home cleaning services saves me time.
		EBF6: Using a sharing platform for home cleaning services helps me find providers efficiently.
Noneconomy benefit [90]	Social benefit	NBF1: Using a sharing platform for home cleaning services allows me to have a more meaningful interaction with others.
		NBF2: Using a sharing platform for home cleaning services promotes my identity among friends.
		NBF3: Using a sharing platform for home cleaning services allows me to develop social relationships.
	Epistemic benefit	NBF4: Using a sharing platform for home cleaning services is a whole new experience.
		NBF5: Using a sharing platform for home cleaning services satisfies my curiosity.
Transaction cost	Searching cost [52]	TCS1: Searching for home cleaning services on a sharing platform saves me time and effort.
		TCS2: Searching for home cleaning services on a sharing platform facilitates the finding process.
	Monitoring cost [91]	TCS3: I can easily monitor the whole transaction process of the home cleaning services through the sharing platform.
		TCS4: The sharing platform saves me time and effort to make sure the transaction of the home cleaning services work well.
	Adapting cost [91]	TCS5: The sharing platform provides me the flexibility to solve any problems with the home cleaning services.
		TCS6: The sharing platform allows me easily change the transaction of the home cleaning services when necessary.
		TCS7: The sharing platform allows me easily adjust any requirement of the home cleaning services when necessary.
Uncertainty [51] [52],	Product uncertainty	UNC1: Compared to traditional services, the degree of uncertainty involved in using the sharing platform for home cleaning services is high.
		UNC2: When using a sharing platform for home cleaning services, it is difficult know whether the service will perform as well as it is supposed to.
		UNC3: When using a sharing platform for home cleaning services, it is difficult to know whether the service will perform as well as others.
	Process uncertainty	UNC4: Compared with traditional services, the degree of process uncertainty involved in using the sharing platform for home cleaning services is high.
		UNC5: Compared with other solutions for home cleaning services, the degree of process uncertainty involved in using the sharing platform is high.
Asset Specificity [51]	Location specificity	SPE1: Location is a main factor when using a sharing platform for home cleaning services.
	Human asset specificity	SPE2: It is important that the service providers have professional knowledge when using a sharing platform for home cleaning services.
		SPE3: Experts are required to help complete the whole transaction when using a sharing platform for home cleaning services.
	Physical asset specificity	SPE4: Additional assets such as hardware or space are required to help complete the whole transaction when using a sharing platform for home cleaning services.
	Dedicated assets	SPE5: Special assets such as specialized equipment are required to help complete the whole transaction when using a sharing platform for home cleaning services.
	Time specificity	SPE6: A particular chance or other temporal considerations affect the traction made on a sharing platform for home cleaning services.
	Brand specificity	SPE7: A particular brand name is a main factor when using a sharing platform for home cleaning services.
		SPE8: The popularity of a brand affects the transaction made on a sharing platform for home cleaning services.

Appendix C. Asset specificity definitions

Type	General definition	Definition in sharing economy
Location	The transaction is closely related to the geographic location. Migration or re-establishment requires high costs.	The location of a product/service provided through the sharing platform affects transaction efficiency. For example, when a user looks for a parking space, the parking space location provided by an owner affects the degree to which the transaction is easily completed.
Human asset	Individuals' skills for products are acquired from work or study. If they are transferred to other jobs or organizations, the productivity may be reduced.	Human expertise is required in a service provided through the sharing platform. The human skills require a long time to accumulate and may not be easily converted.
Physical asset	Assets that require additional investment in order to be productive. Although the asset is moveable, it may be limited to a specific usage.	Users must buy a specific asset for using the service provided by the sharing platform. In other words, users need to purchase additional equipment if they want to adopt services on the platform. For example, the user may need to purchase an additional vacuum cleaner in order to utilize a cleaning service from the platform.
Dedicated asset	Assets are invested for specific trading objects. For example, the production of a certain component may require investment in specialized equipment.	Users may need to deliberately invest in assets in order to use the services provided by the sharing platform. This asset cannot be transferred to other platforms. For example, in order to use the service on the platform, users may need to buy a special mobile phone model, and this phone may not be compatible with other platforms.
Time	The timing of the transaction affects its success or failure.	Services are time specific on the sharing platform. The value of the service is highly dependent on whether the service can be provided to the users within a specified relatively limited period of time.
Brand	The brand itself has created a certain impression and reputation.	The reputation of the service on the sharing platform has a specific value to users. For example, a user may be affected by the brand name that leads to his or her perception of the transaction costs. In addition, the brand is not limited to its brand only but also related to its agency. The reputation of its provider may affect the users' perceptions of the transaction costs

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