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Design of TAM-based Framework for Credibility and Trend Analysis in Sharing Economy: Behavioral Intention and User Experience on Airbnb as an Instance

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Abstract. Sharing economy redefines the meaning of share. Thanks to it, products provided by suppliers may have rather different standards due to their subjective consciousness. This situation brings high pre-purchase uncertainties to consumers, therefore, trust between suppliers and consumers then becomes a key to succeed in the era of sharing economy. Airbnb, one of the platforms that best describes the concept of sharing economy, is taken as an example in this study. Our team designs a series of scenarios and assumptions that follow the criteria of the Technology Acceptance Model (TAM) to find out various factors that affect customer behavioral intentions and prove that trust is the most important factor in the Sharing economy. Both parties, including host and user on the platform, are considered as subjects, and a three-year-long questionnaire test is implemented to collect data from end-users in order to reach an objective conclusion. Partial Least Squares-Structural Equation Modeling is then applied to verify the hypothesis. In addition, consumption is a continuous action, personal experience may also affect trust in the Airbnb and even consumption propensity. Therefore, Multi-Group Analysis (MGA) is used to explore the impact of consumer experience differences on trust and purchase intention. Finally, the results show that the ease of use of the Airbnb Platform has a greater impact on consumer attitude than all of the information on Airbnb, and then have a positive impact on overall behavioral intentions.

Keywords: sharing economy, behavior and trend analysis, TAM model, confirmatory factor analysis, multi-group analysis.

1. Introduction

Rapid development of sharing economy model prompts the redefinition of ownership. This model relates to exploiting profits using the Internet to link between the idling resources and demands of individuals [1]. The ongoing development of web-based information technology has boosted the accessibility of individuals reaching out those who are seeking goods and services [2]. And such phenomenon not only prompts economy development but also changes consumption patterns.

The sharing economy is an economic model in which individuals are able to borrow or rent assets owned by someone else. In other words, the sharing economy has redistributed the resources and promotes its re-sharing and re-use to create new value. However, it is not a new idea, but the reassembly of existing concepts widely applied in many fields. Some of the sharing organizations appeared early before Capitalism, such as charities and religious organizations or in the form of flea markets, swap meets, and second-hand shops...etc. This kind of transaction method can promote the exchange of goods or services between people. However, hinder we didn’t have good communication channels and technology in the past, people just focus on face-to-face consumption and didn't pay attention to it. But it has regained a new impetus through information technology now, especially Web 2.0, mobile technology, and social media now. In 2000, Online peer-to-peer (P2P) marketplaces are growing at a rapid rate, people try to use the Internet to achieve the best use of things. These marketplaces comprise individuals (consumers) who transact directly with other individuals (sellers), while the marketplace platform itself is maintained by a third party [3]. In 2011, the TIME nominated what is now commonly understood as the Sharing Economy as one of “10 ideas that will change the world”. Sharing economy marketplaces have flourished because of network communication technology. And in Europe and the US, the “Sharing Economy”, the new concept of network service technology innovation model, is already flourishing spread globally. For example, Just Park shared the parking space in England, Ola rent transportation in India, Time Republic exchange extra time of labor, and Chegg not only rent textbooks but also help students to find tutors. And in recent years, the sharing economy concept also spread into Asia. Because of the high population and high consumption ability, the Asia market has become an important global economic leader. People also start to have many remaining resources. If these resources can be used well, they must bring Potential risks also are found due to the rapid growth of the sharing economy. Relative to the traditional business model, the warmth of people-to-people conversations cannot be felt. The more important is that the personal subjective cognition or information asymmetry between the seller and the buyer cannot be efficiently solved by actual touch with the product in sharing economy. Under these factors, it becomes more difficult to convince the buyer to trust that this is a good product and to purchase it. So, building trust a strategically important issue at the beginning of the B2C relationship [4]. Especially in the sharing economy, most suppliers mostly operated by individuals, they do not have a strong brand to support their reputation. Therefore, trust is particularly important in the sharing economy. In the era of sharing economy, ‘trust’ has become a kind of quasi-money. It would be difficult in sharing the economy without trust. When strangers shared with each other, greater information transparency let trust stronger. Therefore, the success of the sharing economy depends on establishing mutual trust.

Unlike the vendor-client relationship in the traditional business model, Information Technology (IT) becomes the intermediate, and the only one, that connects buyers and sellers. This intermediate is supposed to prompt interactions between buyers and sellers like a bridge. Therefore, whether this platform is accepted by customers becomes an important key to the success of a transaction. The Technology Acceptance Model (TAM) is a model of user acceptance of information systems technology based on the theory of reasoned action. The first school of thought considers a Web site to be information technology, and as such argues that the same use-antecedents that apply across IT, namely Perceived Usefulness and Perceived Ease of Use as identified by TAM [5-6]. TAM has been used in a variety of studies to explore the factors affecting an individual's use of new technology. Casalo' et al. (2010) also pointed out that consumer participation in online travel communities is affected by Perceived Ease of Use and Perceived Usefulness. Although there are many studies on Airbnb, an explicit and comprehensive understanding of the sharing economy, some literature focus on reputational feedback mechanism or topics related to the nature of peer-to-peer markets. [7-8]. Others focus on the exploratory study in sharing economy or the topic of legal [9-10], but the role of effect on trust to user's Behavioral Intention, is limited [11-12]. C Consequently, the TAM is used to explain whether a trust has an impact on the consumption intentions of Airbnb users in this study. In addition, we believe that consumption is a repetitive behavior, the consumer's attitude and consumption behavior are also indirectly affected by personal experience. E.g., if a customer is cheated in the previous transaction, it may cause customers to avoid using the same platform to consume. Therefore, personal experience will be additionally added to the TAM model to explore whether the difference in experience indirectly affects trust and consumption intentions. Three purposes are pursued as follows.

- To design a theoretical model that explores the effect of the perceived belief for antecedents (i.e., Perceived Usefulness and Perceived Ease of Use) and consequences (i.e., trust and Behavioral Intention)
- To identify the correlations among contexts, provided by/via sharing economy platform (i.e., Airbnb), trustworthiness, and users' experience, and their implicit impacts on user behavior and future purchase intention

The rest of this article is arranged as follows. An overview of the related work is described in Section II. Section III details the proposed model of the research. From the beginning, The TAM model was established according to the research objectives, and hypotheses were established based on this model. Partial Least Squares-Structural Equation Modeling (PLS-SEM) is used to analyze the relationship between hypotheses. Finally, Multi-Group Analysis (MGA) is used to analyze the trust degree and difference according to different user experiences. Section IV goes ahead to discuss the results, and Section V then concentrates on the findings from hypotheses and experiment results. Finally, Section VI then concludes the work and points out potential directions.

2. Related Work

2.1. The importance of trust in Sharing Economy

Sharing economy has become an emerging platform and its growth in various sectors especially in the tourism sector is phenomenal [13-15]. As people 's attention rises, Various surveys and models had been deployed in this area [13-27]. M. Abdar et al. proposed a universal user model to reflect differentially of internal (gender, age, nationality etc.) and external (social media, time, device etc.) factors on crowd's behavior and preference [14]. The statistical and machine learning approach divulged that the users' internal and external factors shared similarity with their behavior pattern. They found that Airbnb users are interested in interactions with host, local culture and unique accommodations of atmosphere and interiors. These three aspects have significance impact on the Airbnb users. Wu et al. [16] explored the purchases made on one of the top short-term rental sites in China called Xiaozhu.com to find the effects of host attributes on such purchases. The data was collected from 935 hosts from Beijing during the period 18th November 2015 to 14th February 2016. The host attributes and their rental characteristics were collected through python powered crawler program. The effects of the attributes were estimated by using Poisson regression model. They found that the key host attributes were gender of the host, personal profile, the number of owned listings, time of reservation confirmation and the acceptance rate. From the sheer volume of reviews about a product on the web, it is difficult to find the true quality of it [17].

Through the above research, Host has a certain influence rate on customer behavior in sharing economy, but as a consumer, it is not easy to perceive real evaluation. Under highly uncertain factors, trust plays a crucial role in developing relationships with customers on this platform [18]. The study by [18] suggested that experience in using the web and a higher degree of trust in e-commerce were the influencing factors of customer's trust. The key factors in this area are user's web experience, technical trustworthiness, site quality and perceived market orientation. Higher level trust in e-commerce makes the people participate in e-commerce. According to their study, the top three risk reduction strategies were partnerships with well-known business partners, money back warranty and positive 'word of mouth'.

The authors in [19] integrated the economic and sociological theories about institution-based trust to recommend that three IT-enabled institutional tactics - credit card guarantees, third-party escrow services and feedback mechanisms – created buyer trust in the group of online auction sellers. Their structural model was supported by the data collected from Amazon's online auction marketplace comprising of 274 buyers. Their study showed that self-reported and actual buyer behaviors were correlated with transaction intentions. Their findings also encompassed that both "strong" (legally binding) and "weak" (market-driven) mechanisms derived from perceived effectiveness of institutional mechanisms. Yang et al. [20] devised a research model to understand the continuance use intention in trust in sharing economy. They integrated Trust Building Model (TBM) with attachment theory and identified trust initiators- affect and cognitive based trust. Their work demonstrated the mediating role of attachment in the relationship between behavioral outcome and trust.

The researchers in [21] revealed that review scores were impossible to differentiate in Airbnb as all hosts obtained maximum values. They investigated the Airbnb databases and found that the guests relied on host's photo as communicating trustworthiness. The hosts who had personal photos were perceived as more trustworthy and had more likely to be booked. In sharing economy transactions, members of both sides must trust one another to perform in good faith. Cheng et al. [22] empirically explored potential guests` trust perceptions in Airbnb via online review contents. They discovered six thematic characteristics of accommodation experiences from the review contents. They found that prominent cognitive themes were repurchase intention, location, host attributes, room description, overall evaluation and room aesthetics. They predicted the trust perceptions by utilizing Convolutional neural network. Zloteanu et al. [23] engendered an artificial sharing economy accommodation platform to study how reputation information and community-generated trust impacted user judgment. They varied the elements concerned to hosts' digital identity, exploiting users' decisions to interact and their perceptions. They came to a conclusion that reputation and trust not only enhanced users` credibility, perceived trustworthiness of hosts but also proclivity to rent a room in their home. Complete profiles or profiles with user selected information had done that effect.

The authors in [24] investigated the trust concept and its temporal C2C relationships with users of Airbnb from the viewpoint of an accommodation provider. They exploited the formation of trust by integrating two antecedents- 'Familiarity with Airbnb.com' and 'Disposition to trust'. Further, they discriminated between 'Trust in renters' and 'Trust in Airbnb.com' and scrutinized their inference on two provider intentions. Their results exhibited that both trust constructs were critical to instigate a sharing deal successfully between two parties. Tussyadiah et al. [25] conducted a multi-stage study to examine how Airbnb hosts eloquent themselves online and how consumer retort to varied host self-presentation blueprint. They found that hosts in Airbnb presented themselves as (1) an individual of a certain profession or (2) a well-traveled individual, enthusiastic to meet new guest. They utilized text mining methods comprising of Airbnb hosts' descriptions from 14 major cities. Consumers responded to the two host self-presentation techniques in a different way and well-traveled hosts demonstrated elevated levels of perceived trustworthiness. The study in [26] investigated sources of distrust in the context of Airbnb. They reviewed the negative comments posted by Airbnb customers on Trustpilot's website. They searched for the keyword 'trust' to mine the negative impact of trust with Airbnb. They extracted 216 negative reviews from the 2733 online reviews. They employed the grounded theory approach which derived two themes that presented the source of distrust: the hosts' unpleasant behavior and Airbnb's poor customer service. The managerial implications were that the customers' concerns should be addressed with positive actions, with prompt apologies and to compensate these customers to negate their distrust. Penz et al. [27] recognized vital aspects of the sharing economy to illustrate its potential in fostering sustainability. It was disparity to applications and definitions of sharing economy models which did not focus on sustainability. Their qualitative and quantitative research examined edifice of communities on consumer side as well as accomplishment of regulations and trust-building in the interaction between consumers and providers in Europe and Asia.

2.2. Trust Analysis Model based on TAM for Sharing Economy

TAM is one of the most commonly-applied theories in the field of information system (IS)/information technology (IT) to examine issues related to usability [28]. Major concepts include: 1) Perceived Ease of Use (PEOU) that presents the extents of user's believe in a system free of effort to use; 2) Perceived Usefulness (PU) that presents the extents of user's believe in a particular system that improves the performance at job; and 3) dependent variable behavioral intention (BI) that presents the extents to which one has devised conscious plans to execute or not in some future behavior.

TAM can be served as a starting point for scrutinizing the effect of external variables that can demonstrate on behavioral intentions [29]. TAM has progressed because of its flexibility via a meticulous development process. The simplicity and the understandability have made TAM one of the extensively used models in the IT research. It can be used to explore user requirement and key features vital for e-services because of its adaptability. Bielefeldt et al. [30] investigated the barriers to participation in the sharing economy. They accomplished a survey in Germany on car sharing. They found that society, personality and firm-related barriers had noteworthy effects on behavioral intention and Attitude that determined participation by employing PLS with structural equation modeling. The authors in [31] devised an empirical analysis model by taking into account the features of sharing economy services. They extended TAM by incorporating perceived enjoyment, reliability and price sensitivity to TAM to derive the key factors that had an effect on the use intention and distinctiveness of services on sharing economy. Their results asserted that use intention, perceived enjoyment, Perceived Ease of Use, Perceived Usefulness, reliability, technology innovation, self-efficacy and price sensitivity exhibited and affected in different ways. The researchers in [32] interviewed 50 drivers who provided service and cars in a digital car-sharing platform. They integrated TAM and Social Exchange Theory (SET) to examine salient motivators in this regard. They presented a motivation model of users' sharing opinion based on Self-determination Theory (SDT) in digital platform besides it. Sun et al. [33] examined the critical factors for lack of adoption in peer-to-peer indirect exchange services. They investigated the usage and attitudes towards peer-to-peer resource sharing sites among 37 New York City residents. Furthermore, they conducted a survey consisting of 195 respondents to determine the function of trust on willingness to lend. They also discussed the non-monetary and monetary structure issues related to adoption. They employed prior research on peer economies and critical mass theory to devise a TAM for indirect exchange systems that incorporated ease of coordination and generalized trust.

Two theoretical models [34] were employed TAM and Diffusion of Innovation Theory to examine consumer adoption of the Uber mobile application. Their results illustrated that social influence, observability, complexity, compatibility and relative advantage had crucial influence on both Perceived Ease of Use and Perceived Usefulness that led to consumer adoption intentions and Attitudes. They combined the two ad-hoc adoption theories. Wang et al. [35] investigated the key factors of the consumers' intention to use ride-sharing services and to promote such services. They extended TAM by utilizing three novel constructs: perceived risk, environmental awareness and personal innovativeness. They surveyed 426 participants with questionnaire and their model based on it was empirically tested. The experimental results showed that Perceived Usefulness, environmental awareness and personal innovativeness had positive association with consumers' intention to hire ride-sharing services while there was negative association between perceived risk and Perceived Usefulness and the intention. Furthermore, personal innovativeness is negatively related to perceived risk, but positively related to Perceived Usefulness.

The current research, including it, has been introduced in the introduction. In addition to the basic discussion of ease of use and usefulness in the application of TAM in Sharing Economics, most of the research focuses on discoursing the impact of the social environment on consumer behavior and recognizing the changes in the overall environment on consumer behavior Most of them show a positive correlation. However, the very important "trust" in e-commerce is rarely discussed. Therefore, this study focuses on whether consumer behavior is affected by trust.

3. Related Method

This section discusses the method applied to examine the effect of the antecedents of the TAM. In addition, discussions on the research model and hypotheses development, data collection, sampling, and questionnaire design, and analytical methods are presented.

3.1. Research Model and Hypotheses

This study proposes a research model and hypotheses development to verify the importance of trust in consumers. To make the research results close to actual consumer behavior, personal experiences are also considered an important factor while discussing. E.g., the satisfaction of previous use, whether the previous transaction encountered a situation, etc. To verify these hypotheses, some constructs are proposed to establish TAM. Fig. 1 shows the research framework based on TAM. Under each of these constructs, there are several indicators with similar properties, which are used to analyze the values of the construct. Table 1 explains the term definition for the pre-defined constructs. Since the purpose of this study is to explore the impact of trust on consumer behavior. This study mainly discusses trust-related issues and understands their relationship with other corresponding constructs. We assume that the results can verify that trust is one of the most important factors affecting consumer behavior in sharing economy.

H1: Airbnb context has a significant positive effect on Perceived Usefulness.
H2: Airbnb context has a significant positive effect on Perceived Ease of Use.
H3: Personal Experience has a significant positive effect on Perceived Usefulness.
H4: Personal Experience has a significant positive effect on Perceived Ease of Use.
H5: Perceived Ease of Use has a significant positive effect on Perceived Usefulness.
H6: Perceived Ease of Use has a significant positive effect on Attitude.
H7: Perceived Usefulness has a significant positive effect on Attitude.
H8: Perceived Usefulness has a significant positive effect on Behavioral Intention.
H9: Attitude has a significant positive effect on Trust on Airbnb and Trust on Host.
H10: Perceived Usefulness has a significant positive effect on Behavioral Intention.

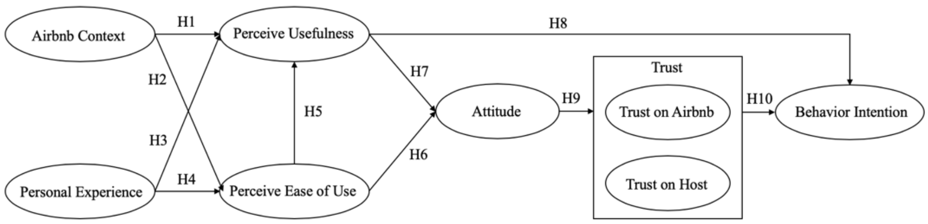

Fig. 1. Research Framework

Table 1. Term Definition of Constructs

Construct	***Definition***
Airbnb Context	All of the hostel Information on the Airbnb platform, including room description, pictures and etc.
Personal Experience	The experience of previous use and motivation of use.
Perceived Ease of Use	Convenience and operation feelings of using the Airbnb interface
Perceived Usefulness	Recognition of using Airbnb to book a room
Attitude	Satisfaction with the Airbnb
Trust	Trust in Airbnb platform and Airbnb Host
Behavioral Intention	Willingness level to use Airbnb again in the future

3.2. Data Collection and Questionnaire Design

Data Collection. In this study, users who had experience in using Airbnb are selected as subjects to conduct the questionnaires. Airbnb is a well-known platform, however, it has been used by fewer people than we expected, so finding people who have used it and are willing to do a questionnaire is also less than we expected. A survey period, in general, is set to three months, but however, the survey period of this study extends to a total period of 21 months (July 2018 to March 2020) by reviewing the collected data every three months, to obtain complete and objective data. Since such data is strongly required because of frequent releases and updates on user interface and service provisions by Airbnb during the above period. The updates may cause especially changes in users' experience and their subjective thoughts on the platform, and wills to continuously stay with the same platform or move to other platforms. The situation in that Airbnb does the updates based on its users' feedback is also taken into consideration. This means that requirements and user experience for the platform have constantly been changing by users. With data collection after a longer period and doing trend analysis, analysis results are more discriminative than the one with data collected within a short period. The questionnaires were mainly distributed via online survey services (i.e., SurveyMonkey, Google Form), but considering recent changes in human behavior that is daily time spent on SNS (Social Network Service) has a sharp growth, reaching more than 2 hours/day [36]. SNS, like Line, Facebook, and WeChat, was also applied to reach as many as possible potential subjects. The questionnaire was distributed to 16 SNS groups. There are about 50-100 members in a group, therefore a total of about 1,200 questionnaires are sent. Among them, about one-fourth of the questionnaires in each group will be completed. Fortunately, a total number of 268 questionnaires were collected and about half of them were confirmed valid to conduct further analysis after excluding those samples with extreme statistical significance.

Questionnaire and Constructs. The research model is based on the extended version of Davis' TAM and is developed to derive the Exogenous variables that affect user Behavioral intention. The TAM model will be used to explain how external variables affect the user acceptance process. In addition, path analysis is applied to explore the empirical strength of the relationship in the proposed model.

Questionnaire Design. Based on the hypothesized model developed, and a detailed review of the related literature on user acceptance of technology, information content, a 37-item questionnaire was devised as a measurement scale for the research. This study uses the Likert seven-point scale, with one - seven points where lower point stands for negative feedback and higher point stands for the positive ones showing as "Strongly Disagree", "Disagree", "Somewhat Disagree", "Neutral", "Somewhat Agree", "Agree", "Strongly Agree".

3.3. Analytical Methods

To assess the overall model of the study, Hair et al. (2017) [37] stages in structural equation modeling (SEM), were adapted. From the result of that literature review, the study incorporated those stages, and the following steps were adopted and implemented in this study. Statistical analysis for the study included descriptive statistics, Confirmatory Factor Analysis (CFA), SEM, and Multi-Group Analysis (MGA). Detailed information for each analysis method is as follows.

Descriptive Statistics. First, this study starts with descriptive statistical analysis that includes gender, age, education, occupation, and annual income. Besides, the study focuses on Asians, therefore questionnaire respondents need to respond to their National. Descriptive analyses are used to determine items of measurement. The mean and standard deviation of variables are used to identify measurement items that are tested on the survey questionnaire in the next stage for overall model testing.

Confirmatory Factor Analysis. CFA is one of the most applied methods which implement by a process to identify the consistency, and relationship as well, between scientific hypotheses and obtained results through the research. CFA is usually implemented by several sequential stages. Different discriminant indicators are usually adopted due to different research purposes and statistical software. This method is applied to models that already have preliminary settings to confirm the fitness between the hypothetical model and the data [38]. Factor loading, convergent validity, and discriminant validity are used to gradually analyze and study the model. In addition, some models, such as Path Analysis/SEM, PLS-SEM etc., are often paired to conduct in the analysis. With the main targets on measurement and structural data model, PLS-SEM is then adopted to conduct the analysis in this research by statistical software, SmartPLS [39].

As above, evaluating the hypothetical model usually begins with factor loading which is the process for observation of correlation(s) between constructs and indicators [40]. Factors that are less relevant to this study have been eliminated. Secondly, the average variance extracted (AVE) is used to identify the convergent validity of the model [41], which is checking the attribute of indicators in each construct is consistent or not. According to the definition, the value of factor loading shall be higher than 0.60, and the value of AVE shall be 0.50 or higher to reach a valid analysis. To show how much variation per node, the square of the indicator's outer loadings which can also show the reliability of indicator is calculated. For exploratory research, we expect the value should close to 0.70, and the higher the better [42-43]. The final step of the CFA process is discriminant validity. The AVE value is checked again. All outer loading must be higher than cross-loadings in models with discriminant validity. This implies that the direct correlation between constructs must be higher than the indirect correlation.

Partial Leased Squares-Structural Equation Modeling. PLS-SEM is a widely applied multivariate analysis method to estimate variance-based structural equation models and become a popular data analysis technique in success factor studies, especially in the application of information system is the most widely used [44]. It also has been used in areas of marketing, enterprise resource planning systems, and knowledge management systems.

PLS-SEM fits especially to those cases with small size of samples, and it meets the requirement of reflective and formative models that contain multiple or single item construct indicators. This method is allowed to model complex relationships among multiple variables. Researchers often use this approach to identify relationships among variables. In short, PLS-SEM is a variance-based method that estimates composites representing latent variables in path models. Based on the information provided in the literature and the intent of the research study, PLS-SEM was used to analyze the data. The significance of the path coefficients was determined by comparing these to the critical t values for significance levels of 0.05 and 0.10. And then the assessment of the structural model, started from obtaining the coefficient of determination (R^2) achieved in the relationship between the independent variables and the dependent variable ranges from 0 to 1 and the closer to 1, the greater the proportion explained. Before testing the model, the data was checked for common method bias. Then, measurement model was examined, followed by structural model.

Multi-Group Analysis. MGA is used to determine whether there are obvious differences in different parameters in the data set (e.g., outer weights, outer loadings, and path coefficients). SmartPLS used in this research provides many MGA methods, e.g., Confidence Intervals (Bias Corrected), Partial Least Squares Multi-Group Analysis (PLS-MGA), etc. Among them, PLS-MGA is often used to determine the difference in path coefficients between different data groups [45]. Therefore, in this study, the PLS-MGA is used to divide the data into two groups (accidents / no accidents when using Airbnb) and investigate whether trust and attitude are significantly affected by different personal experiences.

4. Research Result

4.1. Confirmatory Factor Analysis Results

CFA, as discussed earlier, is to verify the consistency of the hypothetical model and the experimental results. Therefore, we must confirm that each indicator and construct meet the validity standard before verification. The first stage is factor loading that must be measured and used to delete the indicator associated with the lower relationship in construct. Every indicator is analyzed by CFA and must meet the preferred threshold at 0.60. We observed that all indicators reached the boundary threshold except two indicators, PER4 and PER5 with obtained scores at 0.440 and -0.275 respectively. An outer loading relevance test is conducted to determine whether the indicator should be excluded by evaluating each indicator's contribution to the effectiveness of the content [46]. Table 2 presents the results after factor loadings.

Testing internal consistency reliability is the next step. The double verification method [47] is applied to ensure consistency reliability through the values of Cronbach 's Alpha and AVE. Cronbach's Alpha has a required threshold value of 0.70 and higher to show reliability, while the threshold value of AVE should be above 0.50. In terms of consistency reliability, the composite reliability (CR) threshold value, say 0.70 or higher, is used for discrimination.

To ensure the convergent validity is one of the bases of the evaluation model, therefore it should take place in the beginning. Table 3 presents the results of each construct at the convergent validity evaluation. The results indicate that all the constructs fulfill the minimum requirement. The value of Cronbach's Alpha of all constructs are greater than the basic value of 0.70, while the value of AVE reaches 0.80 in average. Although AVE value for construct the personal experience touches 0.582, which is considered lower than others, its value still passes the standard value at 0.50. In addition, it is found that all values reach 0.90, the baseline for CR, and all of them are higher than corresponding Cronbach's Alpha value. This proofs that the model has internal consistency reliability, indicators' properties for all constructs have no direct conflicts in between and demonstrate that our model has discriminant validity.

4.2. Path Analysis

Examining the proposed hypotheses is then conducted after the results of CFA were obtained. Before examining the proposed hypotheses, all constructs that accurately interpret given indicators must be ensured to confirm the predictive capability of our model. Therefore, the value of R2 is used in this step to check the interpretation capability of each construct of our model. As shown in Fig. 2, the R2 value of all structures reaches the given threshold at 0.26 [48]. Next, the PLS-SEM was used to do Path Analysis. To ensure the accuracy of the results, subsamples are used to estimate the PLS path model.

Table 2. Factor Loading for Model

Construct	***Indicators***	***Factor Loading***
Airbnb Context	AC1	0.843
	AC2	0.820
	AC3	0.908
	AC4	0.882
	AC5	0.804
Personal Experience	PER1	0.847
	PER2	0.889
	PER3	0.795
Perceived Ease of Use	EOU1	0.941
	EOU2	0.946
	EOU3	0.918
Perceived Usefulness	PU1	0.957
	PU2	0.962
Attitude	ATT1	0.949
	ATT2	0.933
Trust	TA1	0.891
	TA2	0.892
	TA3	0.909
	TA4	0.826
	TA5	0.862
	TH1	0.890
	TH2	0.912
	TH3	0.827
Behavior Intention	BI1	0.942
	BI2	0.953
	BI3	0.900

Table 3. Measure that Discriminant Validity for Model

Construct	*Cronbach's Alpha*	*AVE*	*CR*
Behavioral Intention	0.924	0.802	0.952
Perceived Ease of Use	0.928	0.811	0.954
Perceived Usefulness	0.914	0.843	0.959
Personal Experience	0.801	0.582	0.882
Airbnb Context	0.906	0.651	0.930
Attitude	0.871	0.778	0.939
Trust	0.962	0.759	0.968

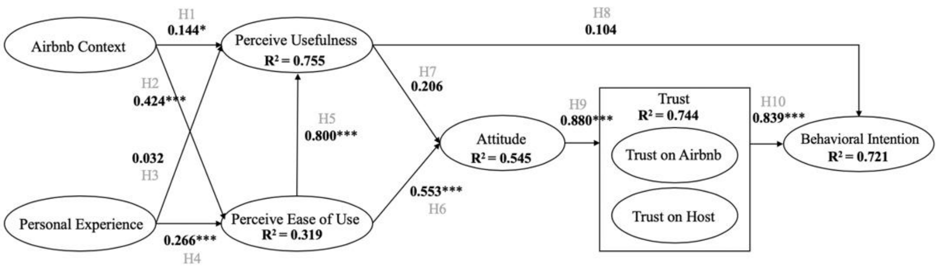

Fig. 2. Result of Path Analysis (*p < 0.05, **p < 0.01, ***p < 0.001)

Table 4. The Result of Path Analysis

		Path Coefficient	t-value	p-value	Hypothesis Testing Result
H1	AC → PU	0.144	1.995	0.046	Accept
H2	AC → EOU	0.424	4.979	0.000	Accept
H3	PER → PU	0.032	0.605	0.545	Reject
H4	PER → EOU	0.266	3.796	0.000	Accept
H5	EOU → PU	0.800	13.313	0.000	Accept
H6	EOU → ATT	0.553	3.350	0.001	Accept
H7	PU → ATT	0.206	1.252	0.211	Reject
H8	PU → BI	0.014	0.134	0.893	Reject
H9	ATT → Trust	0.880	30.889	0.000	Accept
H10	Trust → BI	0.839	9.343	0.000	Accept

Table 5. Constructs and Measurement Items

Indicators		*Measure*
Airbnb Context	AC1	Host provides the number of room's photos and the resolution of those photos which are important information.
	AC2	The brief overviews of the room are important information such as the type of rooms, available number of people, the number of bathrooms/bedrooms, time of check in/out.
	AC3	The amenities of the room that host will provide or not, ex: WIFI, toiletry, breakfast are also an appropriate information.
	AC4	Host set the pricing of room including discounts, extra people, cleaning fee, cancellations fee are important information.
	AC5	The rules of house are important reference.
Personal Experience	PER1	Interface of Airbnb is similar to the website I used before.
	PER2	I use it before and I am satisfied .
	PER3	I use Airbnb because my friend are also using it.
	PER4	Have you ever met the situation below? Advertisement does not match corresponding product
	PER5	Have you ever met any accident during your stays?
Perceived Ease of Use	EOU1	Airbnb is easy to use even for the first time.
	EOU2	Booking rooms on Airbnb is easy.
	EOU3	Information provided by Airbnb makes booking rooms easier.
Perceived Usefulness	PU1	Information provided by Airbnb is useful for users to search and book rooms.
	PU2	Information provided by Airbnb allows me to know that how to search and book rooms more efficiently.
Attitude	ATT1	I think Airbnb is worthy to use for booking rooms.
	ATT2	Using Airbnb for booking hotel is a good idea.
Trust on Airbnb	TA1	Booking on Airbnb is reliable.
	TA2	Accommodation options of Airbnb is trustworthy.
	TA3	Room information is consistent with the facts which is provided by Airbnb.
	TA4	If I required help, Airbnb would do its best to help me.
	TA5	I believe Airbnb would do its best to support me Immediately.
Trust on Host	TH1	The room information is trustworthy which provided by host in Airbnb.
	TH2	The room information with the facts provided by host in Airbnb is consistent.
	TH3	I believe that host in Airbnb can keep its promises and commitments.
Behavior Intention	BI1	I would like to choose Airbnb to collect information when I want to search rooms or make a reservation.
	BI2	I will still choose Airbnb for booking rooms in the future.
	BI3	In the future, I will intend to increase the use of sharing economy platforms.

Table 6. Comparison of MGA Result

	Path Coefficient in no Accident	***Path Coefficient in had Accident***	***Impact percentage***
AC → PU	0.184	0.104	-0.04%
AC → EOU	0.435	0.469	+1.07%
PER → PU	0.049	0.014	-0.72%
PER → EOU	0.292	0.123	-0.42%
EOU → PU	0.791	0.812	+1.02%
EOU → ATT	0.483	0.562	+1.16%
PU → ATT	0.314	0.190	-0.41%
PU → BI	0.111	0.048	-0.57%
ATT → Turst	0.888	0.904	+1.02%
Trust → BI	0.805	0.980	+1.22%

In general, there are 5,000 subsamples randomly generated at this stage. According to the result of Path Analysis, the closer the obtained path coefficient score is to 1, the stronger the relationship will be. Based on the definition, we may find that the weakest relationship is H8 (Perceived Usefulness → Behavioral Intention) with a path coefficient of 0.014 and the strongest relationship is H9 (Attitude → Trust) with a path coefficient of 0.880. This means that in our model, Perceived Usefulness has the least influence on Behavioral Intention, while Attitude has the most influence on Trust.

This concludes that the analysis of the structural model and the hypothesis findings is discussed. According to the definition of SEM analysis, the t-value is required to be greater than the significance level of 1.96 and the p-value shall be less than 0.05 if a hypothesis can be considered valid. This study has a total number of 10 hypotheses. All hypotheses are accepted except H3 ($t = 0.605$, $p = 0.545$), H7 ($t = 1.252$, $p = 0.211$), and H8 ($t = 0.134$, $p = 0.893$). Table 4 provided the results of path analysis and the proposed hypotheses. All results were produced based on bootstrapping with 5000 subsamples. The full names of the abbreviations in the table are as follows: AC= Airbnb Context; PER= Personal Experience; PU= Perceived Usefulness; EOU = Perceived Ease of Use; ATT= Attitude; Trust= Trust on Airbnb and Trust on Host; BI= Behavior Intention. The result show that the most significant hypothesis is H9 ($t = 30.889$, $p = 0.000$), followed by H10 ($t = 9.343$, $p = 0.000$), there is a joint relationship between the two hypotheses, and both are main objective of this study. The detailed questionnaire content is presented on Table 5.

4.3. Multi-Group Analysis

In all consumption behaviors, the user's Attitude will be affected by Personal Experience, especially in the sharing economy that emphasizes trust. Any accident may affect the Trust and consumption tendency. Therefore, this study divides Airbnb consumer data into two categories: (1) Unexpected accidents have been encountered in the use of Airbnb, and (2) No accidents have occurred in the use of Airbnb. And the use of MGA analysis to explore that the Path Coefficient will be affected whether under different personal. In the result of MGA as Table 6, except for the received usefulness in the aforementioned research results, the impact on the model is relatively lower. After consumers encounter unexpected situations in using Airbnb, the ratio of Personal Experience affecting various constructs is low, but the impact of Airbnb content and Ease of Use on construct has improved overall. And Trust has the most impact on Behavioral Intention, which has increased by 1.22%. After encountering an accident, users will rely more on the content and convenience of Airbnb to affect their perception of the Airbnb platform. Behavioral Intention will be affected more by Trust than before.

5. Discussion

The research model for this study was based on the TAM. Airbnb context, Perceived beliefs, Trust are the independent variables, and Behavioral Intention is an outcome variable. For all constructs, there was a combined total of 28 indicators that were analyzed through CFA and PLS-SEM with SmartPLS. Although some revealed issues with factor loading, after amended all the indicators that factor loading, composite reliability, convergent validity, and discriminant validity were in line with the minimum threshold requirements. The findings showed that the model's predictive accuracy and overall significance.

5.1. Research Results and Hypothesis Discussion

As a result, H1, H2, and H4 were accepted, but hypothesis H3 was rejected. The mining of result is that the context of the Airbnb context had a positive and direct effect on Perceived Usefulness and Perceived Ease of Use. Personal Experience has no positive effect on received usefulness. This means that whether before or after use, current users pay more attention to the convenience and ease of use of the platform. The easy-to-use platform makes it easy for users to produce satisfactory Attitude, and then promote the next consumption behavior. These results support previous studies that perceived beliefs are affected by external variables.

Among H5 - H8, only H5 and H6 were accepted, while H7 and H8 were rejected. This shows that received ease of use and attitude and Perceived Usefulness a positive and direct effect. This result means that although received ease of use is helpful to improve the received usefulness, as mentioned earlier, the convenience is paid more attention by consumer now. We believe that such a result is produced because, in this generation of Sharing Economic, the usefulness of the platform has become a basic condition. To win in this fierce competition, the fluency of the platform must be strengthened and improved. Ease of use. E.g., it allows consumers to easily search for the target product during use, and easily go to the checkout page.

H9 and H10 is the focus of this study, and it is also the two most significant assumptions. This shows that the user's Attitude plays a huge role in consumption. It will affect the Trust of the landlord and the platform, which in turn Behavioral Intention will be affected. This result also shows the importance of the platform. The mechanism instant feedback and evaluation are provided in most of the sharing economy platforms. This is to enable the platform to improve according to feedback and reduce information asymmetry with consumers. In turn, Trust is increased. When the platform is Trusted by more and more consumers, the evaluation will be relatively improved, and the willingness to consume will also increase. This result is also consistent with the aforementioned theory, Trust is an important key to affect the sharing economy.

5.2. Result Change Discussion

This study has been updated from the beginning of 2018 to the present. Although the construct of the model has been revised in the course of two years, the basic construct remains unchanged. Therefore, trend analysis was used to analyze the research results of these years to understand the change in consumer behavior. As shown in Fig. 3 below, the main goal in this research, "Trust", has always played an important influencing factor in consumer behavior. And, as the platform grows. As mentioned in related work, a large number of evaluations make it more difficult for consumers to judge the true evaluations, and Trust is increasingly valued in the sharing economy.

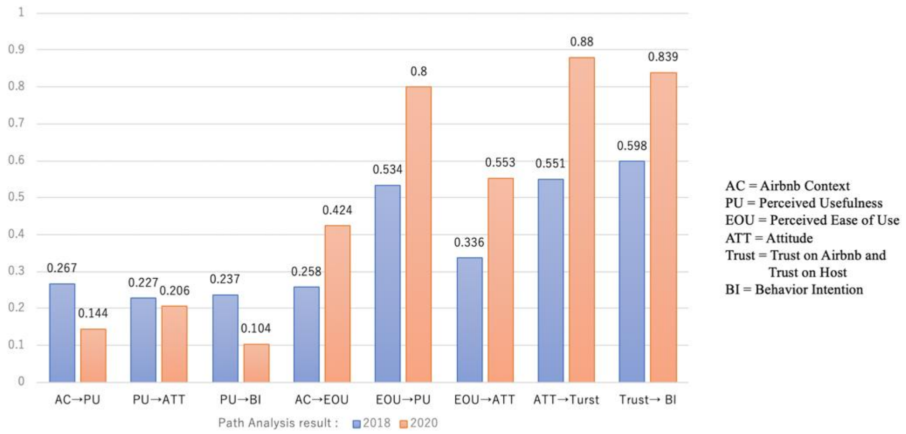

Fig. 3. Compare with Research Result of 2018 and 2020

Interestingly, on the platform side, the impact of Perceived Usefulness in the overall model has declined, and even Airbnb Context has not to effect on the improvement of Perceived Usefulness. However, the impact of the Perceived Ease of Use on model has increased significantly. Except as mentioned earlier, the integrity of all platforms has been improving, Perceived Usefulness has become basic. It also shows changes in consumer behaviors. Accurate and convenient, the impact on consumer behavior is gradually increasing.

This change is also consistent with Airbnb's platform changes in recent years. Airbnb has simplified search content in recent years, with a more intuitive user interface (UI) representation. After searching for listings, in addition to the display of basic listings, the evaluation of the landlord is also replaced with a star rating. If you want to view a more recent review, you need to click on it again. This is to make the booking process faster, the quality of the listing can be understood by the user in a short time, reduce the consumer's consideration time, avoid being reviewed, and increase the chance of the booking being booked.

6. Conclusion

This research builds a theoretical model based on the TAM model. CFA and PLS-SEM statistical methods were used to explore whether several factors such as Trust affects consumer behavior in Airbnb. Factors such as contexts, user experience, perceived beliefs, attitude, trust, and behavioral intention that may cause the changes in usability were especially concentrated. Especially ‘Trust’ is considered the key that decides whether users accept to use sharing economy platforms according to past studies.

To estimate how trust influences Airbnb users, a hybrid TAM model with personal experience as one of the external factors is applied in this study. What can be known is that we usually conducted statistical analysis for a short period of time to conclude their assumptions in the past. However, user behavior should be treated as continuously changing trends from a statistical point of view. The results will be limited if the short period of data collecting. To reach a more objective result close to the situation, this study conducted the trend analysis for a period of approximately 2 years from Summer 2018 to Summer 2020. The issue of trust, according to the obtained results, is still the key factor that affects consumer behavior during the whole period. In addition, the impact of Perceived Ease of Use on consumer intention has significantly grown. While Perceived Usefulness is least impact of consumer intention.

Although Airbnb cannot stand for all the platforms of sharing economy, it indeed shows that it can be one of the most significant platforms in the field. It is foreseen that more and more similar platforms will be developed to meet the various needs of users. Through the results of this study, we are firm that preferences of consumers continue to change, so every platform need to be constantly changed to increase consumer preferences. However, increasing consumer trust level is the best way to increase consumer loyalty to the platform in sharing economy.

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