Revisiting TAM2 in Behavioral Targeting Advertising: A Deep Learning-based Dual-Stage SEM-ANN Analysis

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Abstract

The study investigates the antecedents that affect consumers' acceptance of behavioral targeting advertising (BTA) services by extending technology acceptance Model 2 (TAM2) with perceived risk. A two-stage PLS-SEM-artificial-neural-network (ANN) predictive analytic approach was adopted to analyze the collected data, of which PLS-SEM was first applied to test the hypotheses, followed by the ANN technique to detect the nonlinear effect on the model. A total of 475 usable self-administered questionnaires were collected, and the results showed that only the relationship between the image and perceived usefulness (PU) was not supported. As per Model B, the ranking of subjective norms (SN) and PU between the PLS-SEM and ANN model does not match each other, implying that hidden attributes may exist in affecting the role of SN and PU under the practical context of which the relationship between variables may not fully be explained by a linear perspective. The finding is beneficial for advertising practitioners and software developers who wish to optimize BTA results. Theoretically, the study extends TAM2 in the context of advertising, which is a neglected research area. Methodologically, the study is the first to apply TAM2 using the hybrid PLS-SEM-ANN in the context of advertising.

Keywords – Mobile Advertising, Behavioral Targeting Advertising, Mobile Commerce, TAM, TAM2, Artificial Neural Network

1. Introduction

The use of mobile internet has entered people's daily lives, allowing them to shop, entertain and share information anytime, anywhere. Currently, it is a widely held belief that organizations need to incorporate social media marketing into their overall business strategy to gain significant benefits (Dwivedi et al., 2021). Mobile devices (m-devices) have become a unique channel for commercial organizations and an obvious identifier for users. As researchers point out, "Modern web or mobile applications aim to uniquely identify users to recommend more relevant content and products or display only relevant ads" (Younas et al., 2019, p. 32). Global mobile data traffic is predicted to increase almost sevenfold between 2017 and 2022 (Statista, 2019). As of January 2020, approximately 5.19 billion people, or 67% of the world's population, were active mobile users (Kemp, 2020). Driven by m-device penetration, the estimated global mobile advertising (m-advertising) market size will increase from $44.12 billion in 2008 to $408.58 by 2026 (Fortune Business Insights, 2020). Market size growth and mobile ecosystem improvements create the potential for advertisers to practice targeted advertising, which is considered an effective and valuable method to reach the target audience (Narang and Shankar, 2019).

As an alternative to traditional advertisements, targeted advertising is more efficient in brand building and customer acquisition while also lowering costs (De Vries et al., 2017; Krishen et al., 2021). The targeted advertising of mobile users is achieved by online behavioral targeting (OBT), which is a technique that precisely delivers customized information to mobile users. OBT first collects users' online behaviors, such as web page visits, keyword searching, and shopping records (Li and Nill, 2020), then recommended personalized advertisements based on OBT's algorithm will be delivered to specified mobile users as a result of their behavioral records (Nill and Aalberts, 2014). For example, TikTok collects and analyses users' interactive behaviors, such as video 'likes' and 'shares', followed accounts, comments, and created content, then its recommendation system will deliver short new videos based on interactions (TikTok, 2020). Yu et al. (2020) opined that OBTs promote consumers' product engagement and brand familiarity and increase the click-through rate. Moreover, from a practical point of view, OBTs could enhance the electronic word-of-month of vendors because a successful OBT can be recognized as a reference for consumers to exchange information regarding a product, service, or brand, which facilitates consumers' information seeking (Ismagilova et al., 2021). Wei et al. (2020) argued that consumers prefer customized advertisements rather than random advertisements. Therefore, OBT benefits advertisers by increasing advertising efficiency.

Over the past decade, many types of research have been conducted on behavioral targeting, which includes topics such as behavioral targeting advertising (BTA) effectiveness (Ozcelik and Varnali, 2019) and privacy issues (Estrada-Jiménez et al., 2017; Li and Nill, 2020). However, previous topics in BTA may not explain consumers' BTA decision-making in China, where internet usage has shifted to m-devices such as smartphones. Taking the privacy topic as an example, the study by Estrada-Jiménez et al. (2017) focuses on the privacy matters associated with web-based BTA. On the other hand, Li and Nill (2020) examined the relationship between users' knowledge and the perceived risk of using web based BTA.

Moreover, consumers' acceptance of mobile-based BTA is still less studied. The technology acceptance model (TAM) proposed by Davis (1989) has been widely adopted to investigate users' acceptance of new information systems, such as dynamic web content acceptance on Web 2.0 websites (Wu et al., 2011) and smartphone adoption among high school students (Baudier et al., 2020). However, the original TAM overemphasizes the utilization value of the technology itself rather than viewing technology and the service as a whole solution (Xia and Hou, 2016). Social factors, such as the sense of community, could also affect one's decision-making (Saleh Al-Omoush et al., 2021). Therefore, a broader perspective should be taken when accessing consumers' technology acceptance. The traditional technology acceptance model needs to be integrated with additional factors that highlight the role of users' characteristics (Benbasat and Barki, 2007). In addition, most studies related to the TAM adopted a linear model that ignores the possibility of nonlinear relationships.

To fill these gaps, this study examines the factors that affect BTA usage behavior (UA) by adopting TAM2 using a hybrid partial least squares-structural equation modeling-artificial neural network (PLS-SEM-ANN) approach to capture linear and nonlinear data. Proposed by Venkatesh and Davis (2000), TAM2 extends traditional TAM with social influence constructs and additional cognitive constructs to provide a more comprehensive view of technology acceptance because TAM2 not only focuses on how effective and easy the technology is, but also highlights the role of social influence and personal characteristics in one's decision-making. The TAM2 framework has been widely tested in consumer technology acceptance studies (e.g., Sim et al., 2014) and therefore can be considered a solid framework in information system (IS) adoption research. Risk matter has been widely recognized as one of the most important factors influencing users' decision-making regarding technology acceptance (Saura et al., 2021a; Dwivedi et al., 2020; Wang et al., 2019a), with consumers' perception of risk being influential concerning their intention to adopt mobile-based BTA. Saura et al. (2021b) opined that using user-generated data by commercial organizations has raised the public's concern about users' privacy.

With mobile-based BTA, privacy hazards may create more severe consequences because m-devices record more information than desktop computers. For example, geographic location, photos, and video messages. Therefore, the discussion of BTA acceptance under a mobile setting could differ from a similar topic in a generic online context because not only do the mobile features of devices have a potential influence on users' experiences, but 'privacy' under a mobile context could also reflect the multiple types of information that are more complex than the meaning of privacy under a conventional computer-based online setting. In response to the gaps above, this study investigates the UA of consumers' BTA by extending TAM2 with perceived risk (PR) through the adoption of PLS-SEM-ANN analysis.

2. Literature Review

2.1 Technology Acceptance Model

The technology acceptance model (TAM) proposed by Davis (1989) was derived from the theory of reasoned action (TRA), which is a well-known behavioral theory and has been validated by many widely accepted studies. Chatterjee et al. (2021) opined that the TAM is the most widely adopted model for predicting users' intention and usage behavior in IS acceptance studies. TAM comprises two core constructs: perceived usefulness (PU) and perceived ease of use (PEOU). Previous research has confirmed that both constructs effectively influenced users' attitudes toward whether to adopt a technology. However, the original TAM model is not without drawbacks. Venkatesh et al. (2012) argued that the model is oversimplified and considered insufficient to explain consumer behavior as it relates to real-world practice. Tan and Ooi (2018) agreed with the argument, stressing that the original TAM lacks external variables. According to Legris et al. (2003), the core constructs of the TAM can be further affected by many exogenous variables. For example, Wu et al. (2011) confirmed that individuals' subjective norms might influence their PU, PEOU, and intention to adopt. Moreover, Ooi and Tan (2016) stressed that the original TAM was initially designed to investigate employees' use of technology in the workplace environment, which may not appropriately reflect users' decision-making in consumer scenarios. Kuo and Yen (2009) further commented that TAM could only explain approximately 40% of the variance in the model. The model has also been judged unfavorably by Bagozzi (2007) as having a one-dimensional acceptance construct and, therefore, insufficient to validate the acceptance definition.

Therefore, TAM should be integrated with other external variables to better predict consumer behavior in a modern context (Kiat et al., 2017). Although the original TAM has drawbacks, many previous studies have modified the model by adding new constructs (Magni et al., 2021). For example, in an advertising study, Lin and Kim (2016) extended the TAM model to include cognitive constructs such as privacy concerns and intrusiveness concerns to examine users' attitudes toward online advertising and purchasing behavior. The results suggest that users' privacy and intrusiveness concerns play a negative role in their attitudes toward internet advertising. In another study on short message-based advertising services, Muk and Chung (2015) focused on the extension of TAM constructs with social influence. The results showed that users from a more collective culture, such as China, are more likely to be influenced by the opinions of people around them. Therefore, the extension of TAM can be seen as an objective way to investigate not only the issue of advertising acceptance in general but also the acceptance of BTA from a mobile perspective.

2.2 Technology Acceptance Model (TAM) 2

To cope with TAM's inadequate description of technology acceptance, Venkatesh and Davis (2000) introduced TAM2 by extending the original TAM with seven constructs, including subjective norms, voluntariness, image, job relevance, result demonstrability, output quality, and experience. Wu et al. (2011) noted that the explanatory power of TAM2 is 20% higher than that of the original TAM. TAM 2 has been widely used to study consumers' acceptance of information communication technologies in different fields. Knoesen and Seymour (2019), for example, revealed that TAM2 exogenous variables, such as image, job relevance, and social norms, strongly affect users' perception of usefulness, determining their intention to adopt mobile enterprise applications in South Africa. Additionally, TAM2 has also been validated in many industries, such as e-commerce, agriculture, and health care (e.g., Sharifzadeh et al., 2017; Fidriani et al., 2019; Paramaeswari and Sarno, 2020).

2.3 Behavioral Targeting Advertising (BTA)

Nill and Aalberts (2014) define BTA as a technology that serves consumers with more precise advertisements by tracking and analyzing users' browsing history. The data collected by BTA providers typically includes the visit history of the website, keyword searches, online shopping records, geographic location, and video watching records (Nill and Aalberts, 2014). Halkola (2017) argues that BTA is more effective in influencing users' purchasing decisions than traditional advertisements when online shopping, and consumers' click-through rate is enhanced via the combination of behavioral and contextual targeting (Lu et al., 2016). The argument is also agreed upon by Shareef et al. (2019), who revealed a positive relationship between consumers' perceived advertising value and their attitude toward the advertisement delivered. In addition, prior studies found that more precise content-driven advertisements can affect consumers' brand attitudes and brand memory (Ghosh et al., 2021; Sreejesh et al., 2021). This innovative technique has grown tremendously since BTA achieves a higher return rate on advertisement placement and a lower degree of competition (Zhang and He, 2019).

3. Research Model Development

3.1 Intention to Use (IU)

Users' intention to adopt new IS is attributed to many factors. Lin and Kim (2016) revealed that PU and PEU are important in determining consumers' intention to adopt mobile advertising. Apart from PU and PEU, product ratings are another factor that significantly affects potential consumers' online shopping behavior (Elwalda and Lu, 2016). BTA is more effective than traditional advertisements (Kovčo et al., 2018) by providing more precise advertisements that match the contextual content of information, the value, quality, and experience could significantly impact users' attitudes toward the brand, which contributes to purchasing behavior (Martins et al., 2019). In other words, precise, understandable, and attractive information or advertisements from BTA could lead to consumers taking a more positive outlook toward BTA, thus, contributing to longer daily time spent on the service. As a result, we can assume that when consumers have more intentions to use BTA, they will be more likely to spend more time watching BTA advertisements. Therefore, the following hypothesis is made:

H1: IU has a positive effect on the UB of BTA.

3.2 Subjective Norm (SN)

The concept of SN was initially rooted in the theory of planned behavior developed by Ajzen (1991). Wang et al. (2019b) define SN as people's perception of the social pressure to perform certain behaviors. In addition, Dong et al. (2021) opined that individuals usually see collective judgment and socialization as justifications to assist their own decision-making. SN has been incorporated in research that investigates mobile advertising acceptance. Wong et al. (2015a) found that SN is an important factor in influencing the acceptance of mobile advertising in Malaysia from a social perspective. In addition, Bilgihan et al. (2014) stressed that opinion leaders and interpersonal influences are two key factors that affect the consumer group's information searching and sharing behaviors. Cheung and To (2017) found that SN positively impacts users' intention to watch in-application advertisements. The rationale is that a user may not consider the IU of BTA, but because of the influence of what friends, family members, etc., think, they are likely to agree with the behavior. As such, SN can be considered a potential predictor of an IU adopting BTA. Moreover, Bittner and Schipper (2014) confirmed that SN was positively associated with consumers' PU toward the advertisement of a gamified product; therefore, SN may affect consumers' PU. Similar findings were also established by Wong et al. (2020) on mobile marketing in Malaysia. The image (IMG) is another factor that SN could influence. IMG describes one's social status by reacting to other people's influence. Since individuals usually behave in a way that maintains or enhances their social status (Pfeffer, 1982), SN may positively affect one's image. Based on the logic above, the following hypotheses are proposed:

H2: SN has a positive effect on IU.
H3: SN has a positive effect on PU.
H4: SN has a positive effect on IMG.

3.3 Voluntariness (VOL)

On mobile applications, streaming video advertising tends to force users to watch the ad and then continue watching the video, the majority of users note that this ad disruption bothers them. Kim (2017) explored situations with varying degrees of forced exposure, and experimental results point to the fact that forced advertising resulted in greater relevance and increased ad recall, which may lead to more positive attitudes toward advertising. Venkatesh and Davis (2000) posited that VOL is a construct mainly studied in organizational settings. However, Alwabel and Zeng (2021) argued that this construct can be integrated with models associated with consumer studies because users may give in to adopting technology when they perceive pressures from their society or feel the threat of exclusion. Therefore, the following hypothesis is made:

H5: VOL moderates the relationship between SN and IU.

3.4 Experience (EXP)

Moreover, it has been shown that EXP with the system can influence the acceptance of technology. As EXP increases over time, SN on intention becomes weaker (Hartwick and Barki, 1994). Venkatesh and Davis (2000) found that EXP moderates the relationship between SN and IU. Similarly, the subjective norm influence on PU and IU gradually decreases as users become more knowledgeable about BTA (Venkatesh and Davis, 2000). Following this logic, we proposed the following hypotheses:

H6: Experience moderates the relationship between SN and IU.
H7: Experience moderates the relationship between SN and PU.

3.5 Image (IMG)

Moore and Benbasat (1991, p. 195) define IMG as "the extent to which the use of an innovation is perceived to enhance one's position in the social system". TAM2 suggests that users may adopt certain technology to improve their social status or identity (Venkatesh and Davis, 2000). Furthermore, Alwabel and Zeng (2021) commented that specific technology usage makes users feel that they belong to the same group, and the perception of users' status is enhanced since they are using the technology that the group admires. For example, Long et al. (2019) found that respondents who are familiar with the electric vehicle (EV) brand 'Tesla' are more likely to believe that 'Tesla' vehicles stand for 'the future of EVs' and see themselves as more innovative and stylish. In terms of BTA, users may be more likely to accept this technology, since BTA is a new and rapidly growing advertising technology. As a result, the following hypothesis is proposed:

H8: IMG has a positive effect on PU.

3.6 Job Relevance (JR)

Job relevance refers to "an individual's perception regarding the degree to which the target system applies to his or her job" (Venkatesh and Davis, 2000, p.191). Venkatesh and Davis (2000) regard JR as a cognitive judgment process that directly affects PU but is distinct from the social influence process. The variable is similar to task fit (Goodhue and Thompson, 1995). In the mobile context, when users have a better understanding of the algorithms and data collection process in behavioral targeting, they will be more likely to appreciate the benefits of BTA, which may improve their perception of usefulness in their daily work, such as enhancing an individual's means of obtaining better information. As a result, we proposed the following hypothesis:

H9: JR has a positive effect on PU.

3.7 Output Quality (OQ)

TAM2 suggests that the quality of tasks performed by IS (i.e., output quality; OQ) is another factor of technology acceptance. Davis and Venkatesh (1996) found that an information system's OQ is positively associated with PU. To be more specific, when users perceive the results of the system's performance to significantly contribute to the goal, they are more likely to consider the system useful. Izuagbe and Popoola (2017) found that OQ influences

PU in using electronic resources among library personnel in Nigeria. Therefore, it is necessary to ensure that the outputs from the systems are error-free to create the perception of usefulness. Since BTA usually results in more precise and effective advertisement delivery (Yan et al., 2009), it can be argued that consumer PU will be higher if the perception of OQ is high. As a result, we propose the following hypothesis:

H10: OQ has a positive effect on PU.

3.8 Result Demonstrability (RD)

RD describes the user's perception of adopting the innovation (Moore and Benbasat, 1991). Venkatesh and Davis (2000) stressed that the perceived validity of the results significantly affects the PU. In other words, if potential users perceive that using the system will achieve a promising result, they will be more motivated to accept and use the system. However, if users feel that using the system will not lead to the expected result, they are less likely to adopt it. For example, if the keyword searched on a shopping website is accurate but not relevant to the searching context based on the user's behavioral tag, users will not perceive the advertisement and recommendation system on the site to be useful. Agarwal and Prasad (1997) found a strong association between the demonstrability of the result and the user's intention to use an IS; therefore, RD is likely to affect the user's PU toward BTA. As such, the subsequent hypothesis is proposed:

H11: RD has a positive effect on PU.

3.9 Perceived Ease of Use (PEU)

PEU refers to the extent to which the user believes that adopting IS requires little effort, time, or knowledge (Chong, 2013). Davis (1989) stressed that PEU directly affects PU and has an indirect effect on intention. In the context of mobile devices, the importance of PEUs is further exemplified, as the devices are usually restricted to certain limitations, such as small screen sizes (McLean et al., 2020). Tan et al. (2014) confirmed that PEU has a significant impact on consumers' intention to adopt mobile payment services. Similarly, in mobile advertising, when consumers perceive that performing behaviors such as information searching and purchasing on the shopping website are easy, they are more likely to accept BTA further during their online shopping. Therefore, the following hypotheses are proposed

H12: PEU has a positive effect on IU.
H13: PEU has a positive effect on PU.

3.10 Perceived Usefulness (PU)

PU reflects the perceived degree to which adopting IS will increase task performance (Davis, 1989). More specifically, PU describes users' perception that using the new IS will increase their productivity and save time. Venkatesh and Davis (2000) suggest that PU plays a crucial role in technology acceptance and directly impacts users' intention to adopt. A study conducted by Yan et al. (2021) showed that PU strongly impacts users' behavioral intention toward QR code mobile commerce studies. Moreover, Tan et al. (2018a) found that usefulness significantly affects consumers' intention to use mobile social media advertising. BTA can be seen as an enhancement to obtain more precise information from personalized advertisements based on OBT's algorithm (Siah, 2015). Following the findings of other mobile-based technology studies, it can be assumed that when consumers perceive BTA's advertisement does provide benefits, they are more likely to generate an intention to spend time on BTA. As such, the following hypothesis is proposed:

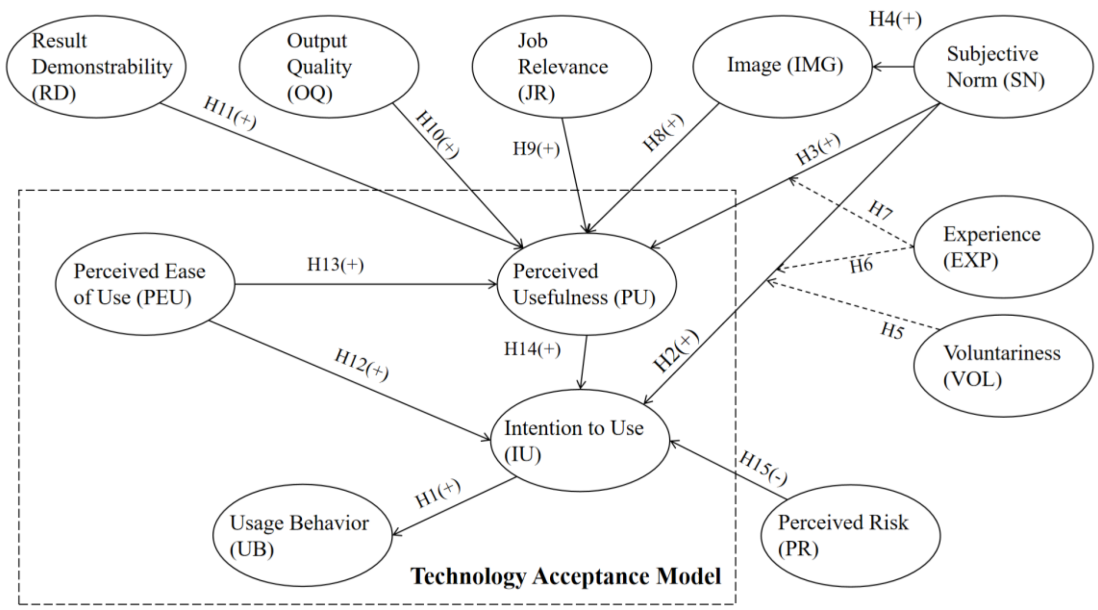
H14: PU has a positive effect on IU.

3.11Perceived Risk (PR)
PR refers to users’ perception of the uncertainties or safety hazards they may face when using new technologies (Nepomuceno et al., 2014). In the present study, we recognize PR as the privacy risks that could occur during BTA data collection, such as the unauthorized disclosure or the theft of users' sensitive information. The role of PR in determining IU has been confirmed by different areas, such as mobile health care (Schnall et al., 2015), online travel (Lin et al., 2009), and social commerce (Saba et al., 2017). As such, based on the studies mentioned above, the following hypothesis is proposed:

H15: PR has a negative effect on IU.

Based on the hypotheses, Figure 1 displays the research model of our study.

Figure 1: Research model



4. Methodology

4.1 Research Instrument
Since the study focused on mobile users, there is no given sampling frame. To meet the purpose of the research, this study applied a convenience sampling technique. A self-administered questionnaire survey was used to collect research data by using validated items from existing studies measured based on a seven-point Likert scale from (1) strongly disagreed to (7) strongly agreed. All the cited items are listed in Table 1:

Table 1: Measurement Items Adopted

Constructs	Number of items	Source
Subjective Norm (SN)	4	Venkatesh and Davis (2000); Martínez-Ruiz et al. (2017)
Perceived Ease of Use (PEU)	4	Venkatesh and Davis (2000)
Perceived Usefulness (PU)	4	Venkatesh and Davis (2000)
Image (IMG)	3	Venkatesh and Davis (2000)
Job Relevance (JR)	2	Venkatesh and Davis (2000)

Output Quality (OQ)	4	Venkatesh and Davis (2000); Barki and Hartwick (2001)
Result Demonstrability (RD)	4	Venkatesh and Davis (2000)
Perceived Risk (PR)	3	Belanche et al. (2012)
Voluntariness (VOL)	3	Venkatesh and Davis (2000)
Experience (EXP)	1	Venkatesh and Davis (2000); Wu et al. (2011)
Intention to Use (IU)	4	Venkatesh and Davis (2000); Martínez-Ruiz et al. (2017)
Usage Behavior (UB)	1	Venkatesh and Davis (2000); Martínez-Ruiz et al. (2017)

4.2 Data Collection and Respondent Profile

Due to the current COVID-19 pandemic, an online questionnaire survey was adopted to avoid potential health hazards caused by face-to-face interaction. The digital questionnaire was distributed through the mobile social networking application known as 'WeChat', which has over 1.1 billion active users monthly (Yu et al., 2020) and has been considered a fast and cost-effective tool in achieving a large sample size by previous researchers (e.g., Zhang et al., 2017; Gan and Li, 2018). Before the formal data collection procedure was conducted, three independent scholars who were advertisement experts evaluated the questionnaire items for content validity. Minor changes to the structure, layout, and language were made. The process was followed by a pilot test based on 30 students to confirm the scale reliability. A total of 475 usable questionnaires were collected from mobile users in China. In this study, we considered China a desirable country for investigating consumers' decision-making on BTA because the total number of mobile-based users had reached 986 million in 2020 (CINIC, 2021), which offers us a representative of the target population. The number of effective responses exceeds the requirement of a minimum sample size of 123 calculated by G*Power (Version 3.1.9.2) with 0.80 power level, 0.05 alpha value, 0.15 impact size, and 11 predictors. As shown in Table. 2, the entire male group accounted for 59.37% of the total sample, while female respondents accounted for 40.63% of the total responses. Most of the respondents were less than 34 years old (73.47%) and had either a diploma (37.89%) or bachelor's level (39.16%), implying that most of the respondents were younger generations who were either students or new working classes in society. Most of the respondents' monthly income was less than RMB 8,000 (75.58%), and most of the population had 3 to 10 years of smartphone usage experience (69.89%). A total of 50.32% of respondents had BTA usage experience between 1 and 7 years (77.48%), and most of the respondents used BTA less than 1 hour per day (90.94%).

Table 2: Demographic Profile

Demographic Characteristics		**Frequency**	**Percentage (%)**
Gender	Male	282	59.37
	Female	193	40.63
Age	18 to 24 years	77	16.20
	25 to 29 years	125	26.32
	30 to 34 years	147	30.95
	40 years and above	71	14.95
Education Background	Primary level or secondary level education	61	12.84
	Diploma or advance diploma level education	180	37.89
	Bachelor's degree level	186	39.16
	Postgraduate level	48	10.11
Personal Income (per Month)	Less than RMB2,000	29	6.11
	RMB2,001 to RMB 5,000	156	32.84
	RMB5,001 to RMB8,000	174	36.63
	RMB8,001 to RM1B15,000	82	17.26
	RMB15,001 to RMB30,000	31	6.53
	More than RMB30,000	3	0.63
Smartphone Usage Experience	Less than three years	31	6.53

	Three to five years	155	32.63
	Six to 10 years	177	37.26
	More than 10 years	112	23.58
BTA Usage Experience	Less than one years	36	7.58
	One to four years	203	42.74
	Five to seven years	165	34.74
	Eight to 10 years	54	11.37
	More than 10 years	17	3.58
BTA Usage Frequency	Less than 20 minutes	134	28.21
	21 to 40 minutes	214	45.05
	41 to 60 minutes	84	17.68
	61 to 90 minutes	34	6.95
	More than 90 minutes	17	2.11

5. Data Analysis

5.1 Statistical analysis

A two-stage PLS-SEM-ANN analytical technique is used to assess the data collected (Sharma et al., 2021). First, PLS-SEM analysis is performed via SmartPLS (version 3.2.9) to predict the proposed model with multifaceted constructs (Ooi and Tan, 2016; Tan et al., 2018b). However, the PLS-SEM technique may not provide a more accurate result, as the variance-based approach ignores the possibility of nonlinear relationships (Leong et al., 2013). As such, the PLS-SEM approach is followed by ANN analysis to identify the potential nonlinear relationships that could affect the results (Leong et al., 2020). Lim et al. (2021) opined that ANN consists of neurons allocated in the input, hidden and output layers of a vast network that does not require researchers to understand the underlying correlations between variables studied. Whereas ANN is also challenged by the 'black box' operation of its algorithm, it may not be applicable to test hypotheses based on parametric assessment (Ooi and Tan, 2016). As such, the combined method PLS-SEM-ANN is adopted to overcome the drawbacks of both PLS-SEM and ANN.

5.2 Common Method Variance

Common method variance (CMV) may exist since this study collects multiple variable data from the same respondent group (Loh et al., 2020). Thus, we checked CMV by following a common method factor analysis proposed by Liang et al. (2007). Table 3 indicates that CMV is less likely to be an issue since the average Ra^2 is larger than Rb^2 with a ratio of 234 (Tew et al., 2021).

Table 3: Common Method Factor Analysis

Indicators	Substantive factor loading (Ra)	Ra^2	Method factor loading (Rb)	Rb^2
IMG1	0.928	0.861	0.000	0.000
IMG2	0.922	0.850	0.031	0.001
IMG3	0.928	0.861	-0.054	0.003
IU1	0.829	0.687	0.000	0.000
IU2	0.818	0.669	0.086	0.007
IU3	0.823	0.677	-0.037	0.001
IU4	0.867	0.752	-0.004	0.000
JR1	0.879	0.773	-0.098	0.010
JR2	0.88	0.774	0.097	0.009
OQ1	0.781	0.610	0.008	0.000
OQ2	0.8	0.640	0.015	0.000
OQ3	0.767	0.588	0.053	0.003
OQ4	0.813	0.661	-0.023	0.001

PEU1	0.784	0.615	0.013	0.000
PEU2	0.766	0.587	-0.013	0.000
PEU3	0.805	0.648	-0.129	0.017
PEU4	0.822	0.676	0.063	0.004
PR1	0.924	0.854	0.091	0.008
PR2	0.92	0.846	-0.032	0.001
PR3	0.926	0.857	0.057	0.003
PU1	0.732	0.536	-0.067	0.004
PU2	0.768	0.590	0.013	0.000
PU3	0.801	0.642	-0.054	0.003
PU4	0.808	0.653	-0.005	0.000
EXP1	0.809	0.654	0.008	0.000
EXP2	0.821	0.674	-0.018	0.000
UB	1.000	1.000	0.011	0.000
RD1	0.825	0.681	0.118	0.014
RD2	0.808	0.653	-0.008	0.000
RD3	0.802	0.643	-0.01	0.000
RD4	0.83	0.689	-0.102	0.010
SN1	0.822	0.676	-0.002	0.000
SN2	0.825	0.681	-0.147	0.022
SN3	0.847	0.717	0.012	0.000
SN4	0.826	0.682	0.118	0.014
VOL1	0.846	0.716	0.029	0.001
VOL2	0.773	0.598	-0.011	0.000
VOL3	0.865	0.748	-0.048	0.002
Average	**0.837**	**0.703**	**-0.001**	**0.003**

5.3 Assessing the Outer Measurement Model

Data reliability is reported in Table 4. Since all the values of Dijkastra-Henseler's rho (rhoA), composite reliability (CR), average variance extracted (AVE), and outer loading exceed the corresponding threshold values of 0.7, 0.81, 0.5 and 0.7, respectively, the data collected are confirmed to have convergent validity (Wong et al., 2015b; Hair et al., 2017). Moreover, Table 5 reports that the heterotrait-monotrait (HTMT) values between some of the latent constructs exceed the strictest criterion (i.e., HTMT<0.85), therefore suggesting that collinearity issues possibly exist (Henseler et al., 2014). However, since none of the lower or upper bounds of the 97.5% confidence intervals were above one, it is still possible to demonstrate that these constructs are empirically distinguished from each other and that the data's discriminant validity is confirmed (Wong et al., 2020).

Table 4: Loadings, Dijkstra Henseler, Composite Reliability and Average Variance Extracted

Constructs	Items	Loadings	Dijkastra-Henseler's rho (rhoA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
IMG	IMG1	0.924	0.919	0.947	0.857
	IMG2	0.927			
	IMG3	0.926			
IU	IU1	0.833	0.856	0.902	0.697
	IU2	0.819			
	IU3	0.818			
	IU4	0.867			

JR	JR1	0.878	0.707	0.872	0.774
	JR2	0.881			
OQ	OQ1	0.796	0.807	0.869	0.624
	OQ2	0.807			
	OQ3	0.744			
	OQ4	0.811			
PEU	PEU1	0.782	0.809	0.872	0.631
	PEU2	0.758			
	PEU3	0.811			
	PEU4	0.825			
PR	PR1	0.923	0.916	0.945	0.852
	PR2	0.916			
	PR3	0.93			
PU	PU1	0.729	0.786	0.860	0.605
	PU2	0.768			
	PU3	0.805			
	PU4	0.807			
EXP	EXP1	0.63	0.717	0.774	0.641
	EXP2	0.94			
UB	UB	1.00	1.00	1.00	1.00
RD	RD1	0.831	0.834	0.889	0.666
	RD2	0.805			
	RD3	0.801			
	RD4	0.827			
SN	SN1	0.824	0.849	0.899	0.689
	SN2	0.827			
	SN3	0.845			
	SN4	0.825			
VOL	VOL1	0.882	0.819	0.865	0.683
	VOL2	0.729			
	VOL3	0.860			

Table 5: Hetero-Trait-Mono-Trait Result (HTMT)

Constructs	IMG	IU	JR	PEU	PR	PU	OQ	RD	SN	UB	VOL	EXP
IMG												
IU	0.300 [0.173, 0.423]											
JR	0.200 [0.059, 0.361]	0.915 [0.833, 0.991]										
PEU	0.334 [0.208, 0.452]	0.766 [0.677, 0.846]	0.771 [0.672, 0.875]									
PR	0.125 [0.038, 0.245]	0.228 [0.097, 0.372]	0.158 [0.045, 0.307]	0.239 [0.117, 0.373]								
PU	0.310 [0.184, 0.429]	0.797 [0.689, 0.893]	0.857 [0.741, 0.971]	0.904 [0.833, 0.968]	0.207 [0.098, 0.342]							
OQ	0.434 [0.324, 0.542]	0.675 [0.562, 0.779]	0.790 [0.658, 0.926]	0.730 [0.628, 0.823]	0.324 [0.204, 0.449]	0.740 [0.622, 0.856]						
RD	0.372 [0.238, 0.492]	0.789 [0.67, 0.893]	0.812 [0.698, 0.923]	0.715 [0.596, 0.827]	0.222 [0.100, 0.361]	0.753 [0.657, 0.846]	0.785 [0.679, 0.884]					
SN	0.278 [0.140, 0.41]	0.695 [0.581, 0.804]	0.813 [0.719, 0.915]	0.690 [0.573, 0.791]	0.193 [0.084, 0.330]	0.886 [0.820, 0.954]	0.626 [0.519, 0.729]	0.708 [0.600, 0.802]				
UB	0.062 [0.013, 0.162]	0.127 [0.052, 0.225]	0.078 [0.029, 0.167]	0.166 [0.06, 0.275]	0.019 [0.012, 0.130]	0.102 [0.032, 0.216]	0.054 [0.027, 0.176]	0.129 [0.047, 0.236]	0.064 [0.026, 0.185]			
VOL	0.276 [0.142, 0.416]	0.599 [0.460, 0.737]	0.496 [0.341, 0.659]	0.369 [0.230, 0.518]	0.405 [0.270, 0.545]	0.453 [0.310, 0.603]	0.425 [0.292, 0.576]	0.567 [0.418, 0.709]	0.496 [0.357, 0.638]	0.053 [0.019, 0.163]		
EXP	0.066 [0.038, 0.217]	0.191 [0.102, 0.344]	0.183 [0.084, 0.379]	0.288 [0.144, 0.453]	0.154 [0.082, 0.269]	0.232 [0.124, 0.393]	0.191 [0.091, 0.361]	0.194 [0.107, 0.352]	0.115 [0.063, 0.264]	0.279 [0.197, 0.442]	0.180 [0.114, 0.303]	

5.5 Inspecting the Inner Structural Model

A bias-corrected and accelerated (BCa) bootstrapping approach based on 5,000 subsamples with a two-tailed 0.05 p value was adopted to identify the significant path coefficients of the inner structural model (Ooi et al., 2020). According to both Table 6 and Figure 2, among all the tested hypotheses, only H8, H10, H11 and 15 are not supported. IU ($\beta = 0.116$, $p < 0.05$) has a strong and positive correlation with UB, suggesting that H1 is supported. In addition, SN ($\beta = 0.113$, $p < 0.05$), PEU ($\beta = 0.315$, $p < 0.001$) and PU ($\beta = 0.228$, $p < 0.05$) are positively associated with IU, which confirms that H2, H12 and H14 are supported. SN ($\beta = 0.36$, $p < 0.001$), JR ($\beta = 0.14$, $p < 0.001$) and PEU ($\beta = 0.353$, $p < 0.001$) are observed with strong and positive influences on PU, indicating that H3, H9 and H13 are supported. Last, SN ($\beta = 0.246$, $p < 0.001$) shows a significant positive effect on IMG, supporting H4. Overall, the model effectively explains 14% of the variance in BI. In addition, the PU, PEU and SN can explain 56.9% of the changes in UI; JR, SN and PEU can explain 68.5% of the changes in PU, and SN is able to explain 60% of the changes in IMG.

Figure 2: Result of Hypothesis Testing

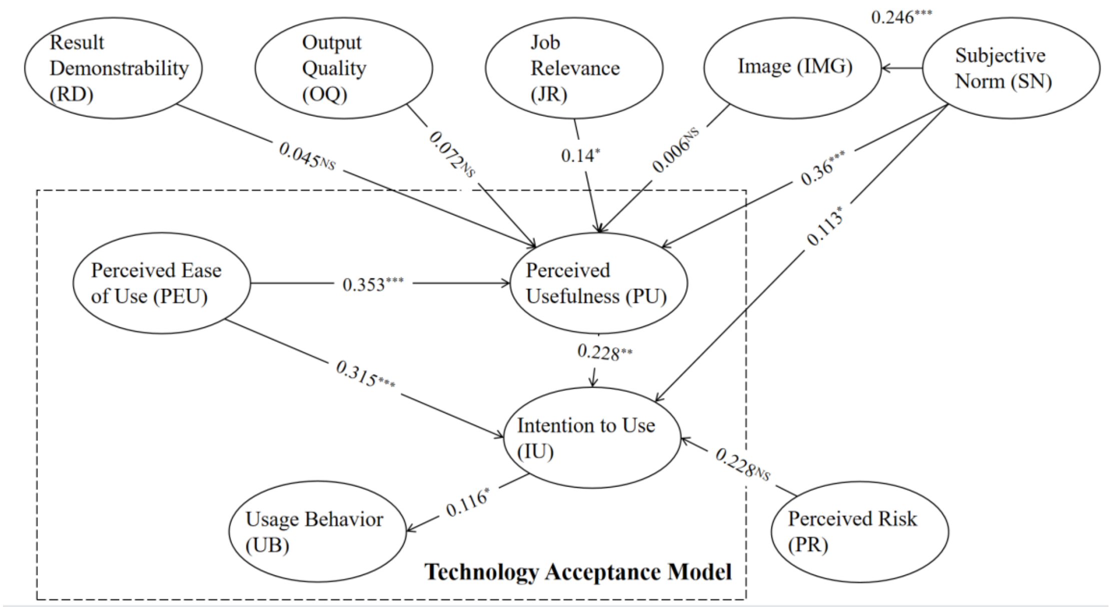


Table 6: Structural Model Examination Outcome

Hypotheses	Path Coefficients	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Remarks
H1	Intention to Use (IU) -> Usage Behavior (UB)	0.116	0.116	0.048	2.416	0.016	Supported
H2	Subjective Norm (SN) -> Intention to Use (IU)	0.113	0.116	0.076	1.473	0.141	Supported
H3	Subjective Norm (SN) -> Perceived Usefulness (PU)	0.360	0.362	0.052	6.892	0.000	Supported
H4	Subjective	0.246	0.247	0.060	4.101	0.000	Supported

	Norm (SN) -> Image (IMG)						
H8	Image (IMG) -> Perceived Usefulness (PU)	0.006	0.006	0.039	0.152	0.879	Not Supported
H9	Job Relevance (JR) -> Perceived Usefulness (PU)	0.140	0.139	0.063	2.209	0.027	Supported
H10	Qutput Quality (OQ) -> Perceived Usefulness (PU)	0.072	0.074	0.063	1.130	0.259	Not Supported
H11	Result Demonstrability (RD) -> Perceived Usefulness (PU)	0.045	0.045	0.056	0.804	0.422	Not Supported
H12	Perceived Ease of Use (PEU) -> Intention to Use (IU)	0.315	0.304	0.066	4.798	0.000	Supported
H13	Perceived Ease of Use (PEU) -> Perceived Usefulness (PU)	0.353	0.350	0.056	6.337	0.000	Supported
H14	Perceived Usefulness (PU) -> Intention to Use (IU)	0.228	0.229	0.086	2.661	0.008	Supported
H15	Perceived Risk (PR) -> Intention to Use (IU)	-0.007	-0.007	0.042	0.164	0.870	Not Supported

Remarks: *p <0.05; **p <0.01; ***p <0.001; ^{NS} Not supported

5.6 Assessing the Moderating Effects

Moderated PLS-SEM was employed to examine the moderating effects of EXP and VOL in this study. As shown in Table 7, the results indicated that the relationship between SN and IU is not moderated by either EXP or VOL, and EXP was found to have no significant effect on moderating SN to PU. Hence, H5, H6 and H7 were all rejected. The result suggests that with or without experience, the relationship between consumers' SN and PU and SN and IU will not change significantly. On the other hand, consumer differences in willingness to volunteer will not create a tendency to perceive SN as a factor that influences the intention to adopt BTA.

Table 7: Hypothesis Testing for Moderating Effect

Hypotheses	Path Coefficients	Path Coefficients	T Statistics	P Values	Confidence Interval (2.50%)	Confidence Interval (97.50%)	Remarks
H6	EXP*SN -> IU	-0.008	0.147	0.883	-0.131	0.081	Not Supported
H7	EXP*SN -> PU	-0.016	0.401	0.689	-0.092	0.066	Not Supported
H5	VOL*SN -> IU	-0.047	0.875	0.382	-0.149	0.052	Not Supported

5.7 Predictive Relevance, Effect Size and PLSPredict

This study adopts the optimum approach recommended by Hair et al. (2017) to assess the predictive relevance of the research model. Based on Table 8, it can be concluded that the model shows predictive relevance since all the Stone-Geisser's Q^2 calculated by the cross-validated redundancy are greater than zero (Cohen, 2013; Lew et al., 2020). In terms of the effect size, the intensity of variables' relationship is assessed by f^2 (Cohen, 2013), whereby 0.02, 0.15 and 0.35 indicate small effect, medium effect, and large effect, respectively. According to Table 9, the results show that both PEU and SN have a high effect on PU. In addition, SN has a medium effect on IMG; PEU, PU and VOL have a medium effect on IU. However, other paths are only observed with small or no effects. Moreover, since Loh et al. (2019) opine that R^2 also focuses on the model's in-sample explanatory power, the PLS prediction technique is also adopted to assess the out-of-sample power. As per Table 10, UB indicates a positive Q^2 prediction value, but the root mean squared error (RMSE) in PLS-SEM is larger than the RMSE value in the linear model benchmark. The model is viewed as having weak predictive power.

Table 8: Predictive Relevance, Q^2

Endogenous Construct	Q^2	Predictive Relevance
Image (IMG)	0.044	$Q^2 > 0$
Intention to Use (IU)	0.364	$Q^2 > 0$
Perceived Usefulness (PU)	0.383	$Q^2 > 0$
Usage Behavior (UB)	0.008	$Q^2 > 0$

Table 9: Effect Size (f^2)

Predictors/Dependent Constructs	**IMG**	**IU**	**PU**	**UB**
EXP		0.02	0.034	
IMG			0.006	
IU				0.116
JR			0.14	
PEU		0.315	0.353	
PR		-0.007		
PU		0.228		
OQ			0.072	
RD			0.045	
SN	0.246	0.113	0.36	
VOL		0.262		

Table 10: PLSpredict Result

Construct	**PLS-SEM**			**Liner Model Benchmark**	
	RMSE	MAE	Q^2_predict	RMSE	MAE
UB	0.958	0.69	0.01	0.952	0.738

5.8 Importance Performance Map Analysis

The purpose of IPMA is to detect the constructs that have high importance in the targeted variables yet underperform (Ringle and Sarstedt, 2016). Both Table 10 and Figure 3 present the IPMA results associated with UB. The construct with the highest importance on UB is IU (0.116), followed by PEU (0.046) and PU (0.026). Moreover, SN (0.023) is also of relatively high importance compared to the rest of the constructs in the model. On the other hand, JR (81.089) indicates the highest performance, followed by SN (78.717) and RD (78.427).

Table 11: Importance Performance Map Results

Latent Variables	Importance (Total Effect)	Performance (Index Value)
Experience (EXP)	0.003	47.110
Image (IMG)	0.000	65.527
Intention to Use (IU)	0.116	77.663
Job Relevance (JR)	0.004	81.089
Perceived Ease of Use (PEU)	0.046	74.934
Perceived Risk (PR)	-0.001	71.455
Perceived Usefulness (PU)	0.026	78.139
Output Quality (OQ)	0.002	73.012
Result Demonstrability (RD)	0.001	78.427
Subjective Norm (SN)	0.023	78.717
Voluntariness (VOL)	0.030	72.695

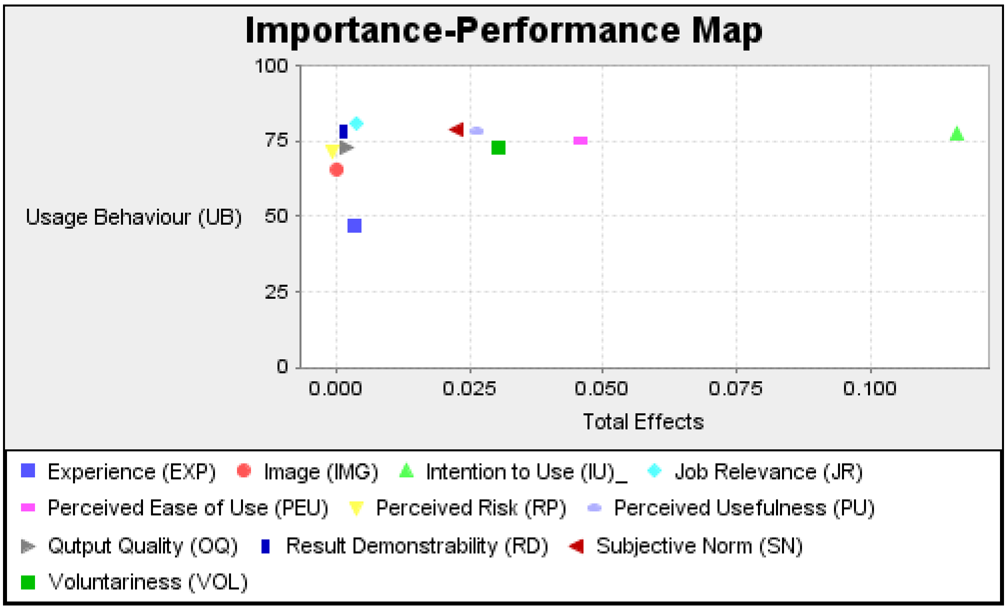


Figure 3: IPMA for UB

5.9 Artificial Neural Networking (ANN) Analysis

In business research, ANNs can be recognized as algorithms that model the mechanism in which humans perform tasks or make decisions (Haykin, 2004). Unlike conventional regression-type models, ANNs will not be affected by collinear independent variables and do not need linearity assumptions when predicting dependent variables based on multifaceted inputs (Wilson and Bettis-Outland, 2019). This study adopts a feed-forward-back-propagation (FFBP) multilayer perceptron (MLP) technique in training the data and assessing the relative importance of the predictors. A 10-fold cross-validation approach with 90% data for training and 10% data for testing is developed to reduce the issue caused by overfitting. The hidden and output layers of the ANN model are automatically generated via SPSS and activated by the sigmoid function. RMSE values are assessed to confirm the predictive accuracy, which is presented in Table 11. Since the RMSE values in all the ANN models are small, it can be concluded that the models have a high degree of predictive accuracy. Table 12 presents the power of predictors in ANN models. To assess the contribution of each predictor in cultivating UB in TBA, normalized importance based on percentage was calculated using the relative importance of each predictor divided by the largest relative importance among all the predictors in each ANN model (Leong et al., 2020). The results indicate that SN had the strongest power in predicting PU, followed by PEU. On the other hand, PEU exhibits the strongest prediction of IU, followed by SN and PU. Since IU and SN are the only predictors for UB and IMG, both predictors are considered 100% normalized importance. The four ANN models engaged in the sensitivity analysis are listed in Figure 4. Finally, Table 13 ranks and compares the significant predictors in the research model. The ranking results of PLS-SEM are based on path coefficients, whereas the ranking of predictors in ANN models is built by normalized relative importance. As per Model B, the ranking of SN and PU between the PLS-SEM and ANN model do not match each other, implying that hidden attributes may exist in affecting the role of SN and PU under the practical context of which the relationship between variables may not fully be explained by a linear perspective.

Table 11: RMSE value of ANN models

	Model A **Input: SN, JR, PEU** **Output: PU**		**Model B** **Input: SN, PU, PEU** **Output: IU**		**Model C** **Input: IU** **Output: UB**		**Model D** **Input: SN** **Output: IMG**	
Neural network	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN1	0.070	0.066	0.090	0.092	0.168	0.191	0.161	0.143
ANN2	0.069	0.090	0.084	0.131	0.170	0.148	0.154	0.148
ANN3	0.069	0.079	0.094	0.057	0.171	0.129	0.162	0.156
ANN4	0.078	0.047	0.096	0.078	0.165	0.215	0.157	0.142
ANN5	0.072	0.051	0.090	0.094	0.170	0.129	0.159	0.149
ANN6	0.070	0.058	0.098	0.106	0.165	0.178	0.154	0.138
ANN7	0.069	0.065	0.099	0.069	0.168	0.157	0.155	0.135
ANN8	0.069	0.069	0.101	0.091	0.162	0.213	0.161	0.172
ANN9	0.070	0.066	0.096	0.074	0.167	0.171	0.155	0.146
ANN10	0.071	0.069	0.093	0.078	0.168	0.169	0.155	0.157
Mean	0.071	0.066	0.094	0.087	0.167	0.170	0.157	0.149
SD	0.003	0.012	0.005	0.021	0.003	0.031	0.003	0.011

Table 12: Sensitivity Analysis

		Output: PU			**Output: IU**		**Output: UB**	**Output: IMG**
Neural network	**SN**	**JR**	**PEU**	**SN**	**PEU**	**PU**	**IU**	**SN**
ANN1	0.408	0.206	0.386	0.413	0.232	0.354	1.000	1.000
ANN2	0.500	0.069	0.431	0.261	0.398	0.341	1.000	1.000
ANN3	0.484	0.098	0.418	0.364	0.323	0.312	1.000	1.000

ANN4	0.389	0.253	0.358	0.336	0.347	0.316	1.000	1.000
ANN5	0.485	0.113	0.403	0.378	0.496	0.127	1.000	1.000
ANN6	0.459	0.137	0.404	0.292	0.375	0.332	1.000	1.000
ANN7	0.453	0.136	0.411	0.310	0.309	0.381	1.000	1.000
ANN8	0.430	0.146	0.423	0.359	0.334	0.307	1.000	1.000
ANN9	0.456	0.091	0.453	0.325	0.382	0.293	1.000	1.000
ANN10	0.486	0.093	0.421	0.375	0.384	0.241	1.000	1.000
Average relative importance	0.455	0.134	0.411	0.341	0.358	0.300	1.000	1.000
Normalized relative importance (%)	100.000	29.495	90.286	95.335	100.000	83.911	100.000	100.000

Table 13: PLS-SEN and ANN results comparison

PLS Path	Original Sample (O)/ Path Coefficient	ANN Results: Normalised Relative Importance (%)	PLS-SEM Ranking based on Path Coefficient	ANN Ranking based on Normalised Relative Importance (%)	Remark
Model A (Output: PU)					
SN->PU	0.36	100	1	1	Matched
JR->PU	0.14	29.495	3	3	
PEU->PU	0.353	90.286	2	2	
Model B (Output: IU)					
SN->IU	0.113	95.335	3	2	Not Match
PEU->IU	0.315	100	1	1	Matched
PU->IU	0.228	83.911	2	3	Not Match
Model C (Output: UB)					
IU->UB	1	100	1	1	Matched
Model D (Output: IMG)					
SN->IMG	1	100	1	1	Matched

Figure 4: ANN Model A for PU

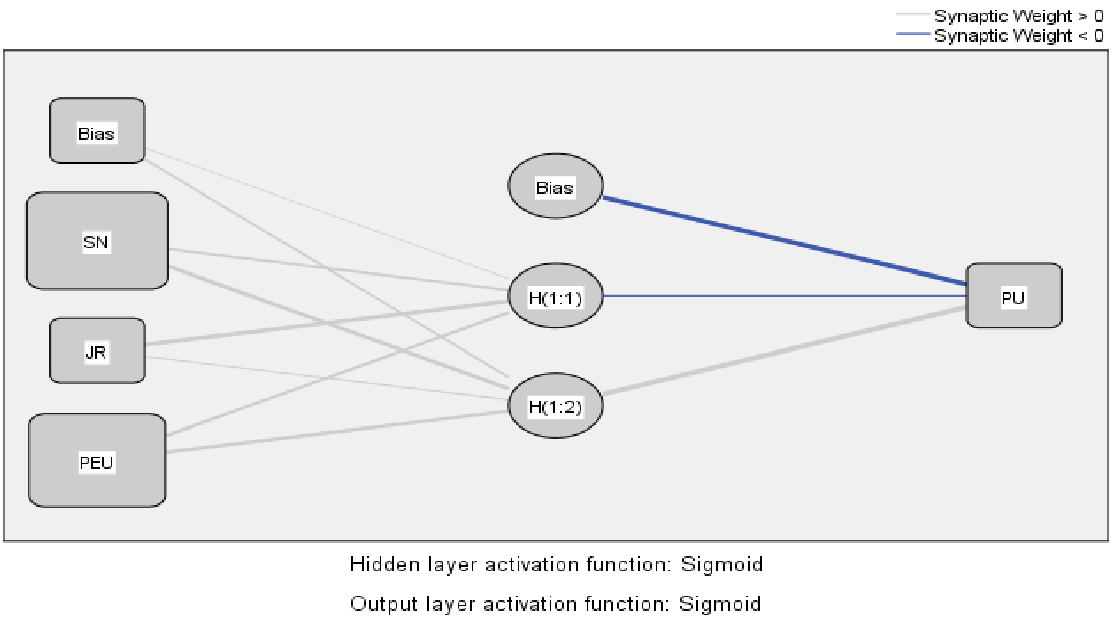


Figure 5: ANN Model B for IU

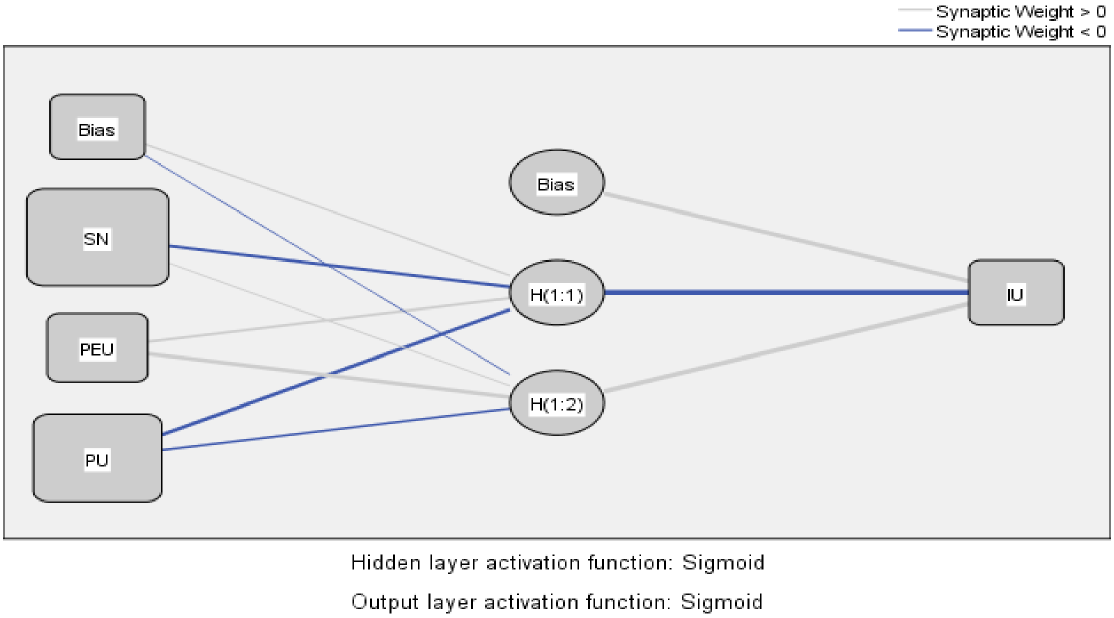


Figure 6: ANN Model C for UB

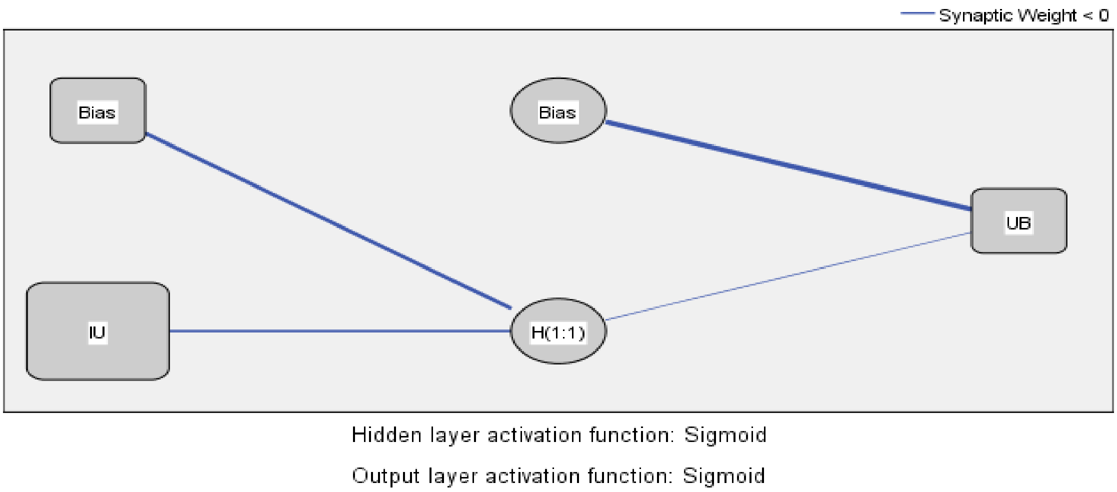
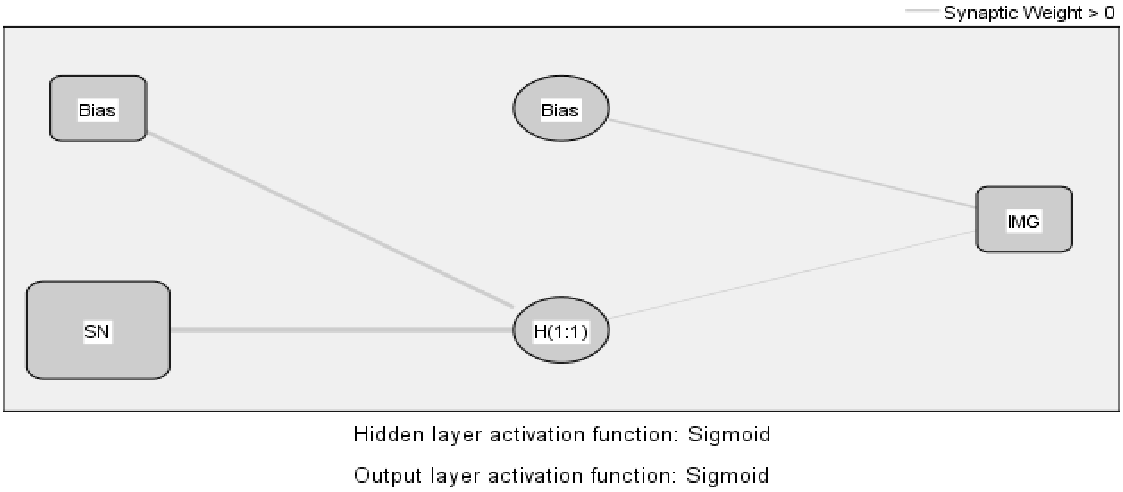


Figure 7: ANN Model D for IMG



6. Discussions and Implications

This study aims to investigate the antecedents that affect consumers' decision-making regarding BTA services. A significant relationship is observed between consumers' intention to adopt BTA (IU) and actual usage behavior (UB), suggesting H1 is supported. Cheung and To (2017) stressed that users with higher intentions to watch in-app advertising are more willing to maintain the behavior. Additionally, the results agree with Sharifzadeh et al. (2017), who found a strong relationship between IU and subsequent usage behavior. A significant positive relationship is found between SN and IU, which confirms H2. This finding is in line with Nwagwu and Famiyesin (2016), who revealed that SN affects consumers' intention to positively adopt mobile advertising. A similar relationship is also reported by Cheung and To (2017), in which SN enhanced users' in-app ad watching behavior. In other words, the word-of-mouth effect from the initial adopters can spread to potential users within a short period of time. SN had a significant and positive relationship with PU; thus, H3 is also confirmed. A similar relationship between the two constructs has been validated between SNs and consumers' perception of using mobile payment systems (Teo and Zhou, 2014). SN is also positively associated with the user's image (IMG), whereby H4 is supported. This finding corresponds with that of Venkatesh and Davis (2000), who opined that positive influences from others would enhance one's perception of self-image. JR indicates a significant positive impact on PU, suggesting that H9 is supported. Since JR reflects users' perception of how new technology will be applied to their work (Venkatesh and Davis, 2000), users' judgment of JR will affect their perception of usefulness. Furthermore, PEU has significant and positive effects on both IU and PU, supporting H12 and H13. Many previous studies have confirmed the role of PEU in determining IU (e.g., Lee et al., 2010; Tan et al., 2014). Lee et al. (2010) argued that PEU was a key predictor of intention for adopting plasma etching using the TAM framework. In the BTA context, the results imply that users are more likely to be motivated to use it. The relationship between PU and IU is also positive and significant, suggesting that H14 is supported. This finding is supported by many earlier studies, such as Tan et al. (2014) and Jaradat and Mashaqba (2014). Loh et al. (2019) argue that users will assess whether the added advantages of innovation outweigh those of conventional alternatives when deciding whether to accept it. Therefore, BTA's added benefits could be a factor in motivating consumers' acceptance.

Apart from the supported hypotheses, H8, H10, H11, H15,the moderating effects (H5, H6, H7) are not supported. The insignificant relationship between IMG and PU (H8) contradicts Venkatesh and Davis (2000), who posited and confirmed a positive and significant relationship between the two constructs by studying technology acceptance in a working context. However, social influence may not be strong enough in buffing BTA users' perception of usefulness in the context of consumption. In addition, H10 is not supported, which implies that OQ in BTA may not affect the user's perceived usefulness. Unlike other types of mobile technology, such as mobile payments, the output quality of BTA may not be intuitively assessed by the user; therefore, the usefulness of BTA may not be easily perceived. Similarly, the relationship between RD and PU is also insignificant. Since the BTA algorithm captures diversified information from users, the advertisement delivered to consumers may not perfectly match consumers' needs. In addition, in situations where consumers generate new needs, BTA may not provide accurate information since there are no relevant data that can be used for predicting consumers' shopping behavior. PR is another variable that indicates no significant impact on IU; thus, H15 is not supported. The insignificant relationship is also confirmed by Lin et al. (2017), who found that PR does not influence consumers' attitudes toward mobile advertising acceptance. This implies that consumers may be more likely to recognize privacy as an important issue in the context where privacy disclosure can lead to monetary loss (Karjaluoto et al., 2019). In the BTA context, the simple disclosure of shopping records or search history is unlikely to result in monetary loss directly; therefore, PR may not be considered a factor that stops users from accepting BTA.

All the moderating effects posited in this study are unsupported. Although BTA is more innovative than conventional advertisements, it is still a one-way communication channel. The user is still forced to watch. For example, the accurate advertisement popped up halfway through a YouTube video. Therefore, it could be difficult to assess the role of VOL in situations in which information is randomly exposed, as such H5 is rejected. EXP is another factor that failed to moderate the relationships in the model. This finding aligns with Venkatesh et al. (2012), who found that EXP has no effects in moderating the paths to IU. In mobile BTA, users are the pure receiver rather than the party that can engage in positive ways. As such, having or without user experience is unlikely to create obvious influences on BTA. Following this logic, H6 and H7 are not supported.

From a theoretical perspective, this study extends the borders of mobile advertising research by integrating TAM2 with BTA, which is still new to advertising research. Since many previous studies have highlighted the role of privacy matters in mobile technology acceptance (see, e.g., Wang et al., 2019a; Hew et al., 2019), this study contributes to the field by introducing PR as a new variable for TAM2. Considering that mobile privacy contains data not only in the form of character messages but also in other types, such as video, location, and photos, consumers may not fully realize how their data will be used and what privacy hazards may look like. By introducing PR in the BTA context, this study offers a new perspective for future researchers in emerging and established markets to consider how the dangers of different privacy expectations would affect consumers' decision-making toward new mobile technologies, which are validated by linear and nonlinear relationships. Moreover, the model incorporates concepts such as external influences and social norms with intention and actual usage behavior to explain consumer decision-making in BTA. The findings of this study fill the knowledge gap in mobile users' acceptance of BTA and provide theoretical references for further research into similar topics.

This finding suggests that more attention should be given to highlighting the social influence that changes people's opinions toward BTA in terms of practical contributions. For instance, BTA providers may enhance the socialization properties of advertisements by allowing users to share their product experiences or reviews. By doing so, not only can the 'word-of-mouth' effect be used as a social influence to facilitate technology acceptance (Mishra et al., 2021), but users may also perceive that the product in BTA is 'real' and can fulfil their needs. Additionally, the finding on JR implies that an advertising company should design their advertisements with a logic that makes it easy for the audience to perceive better

JR. By doing so, the consumer would believe BTA is relevant to their future purchasing behavior, therefore considering BTA as a useful way to benefit the shopping experience. The insignificant role of consumer voluntariness suggests that BTA is still a mandatory service with a lack of interaction between provider and consumer. As such, enhancing consumers' engagement could lead to a more positive attitude toward accepting and embracing BTA.

7. Limitations and Recommendations

Since the study was conducted in China's context, the results of this study may not reflect the adoption of mobile-based BTA in other countries. Future studies could consider the role of culture in technology acceptance. Jin et al. (2008) believe that cultural differences are the major barriers that hinder the development of effective products and services. Studies conducted at the national level or in multiple countries would allow scholars to better understand the relevant issues. In addition, this study only brings PR into the TAM2 framework. To overcome this limitation, future studies could include other variables that influence the adoption of BTA.

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