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Intention to Adopt AI-Powered Online Service Among Tourism and Hospitality Companies

Yi-Hui Ho, Chang Jung Christian University, Taiwan
Syed Shah Alam, Universiti Kebangsaan Malaysia, Malaysia
Mohammad Masukujjaman, Northern University, Bangladesh
Chieh-Yu Lin, Chang Jung Christian University, Taiwan*
https://orcid.org/0000-0003-3393-9674
Samiha Susmit, Universiti Kebangsaan Malaysia, Malaysia
Sumaiya Susmit, Universiti Teknologi Malaysia, Malaysia

ABSTRACT

This study examines the factors affecting the adoption of artificial intelligence (AI)-powered online services in the tourism and hospitality sector through an extension of the technology acceptance model (TAM) by including self-efficacy, subjective norms, technological knowledge, and perceived cost in the analysis. Data were collected from 336 respondents in Malaysia's tourism and hospitality industry using the questionnaire survey. The empirical results confirmed that perceived usefulness, ease of use, attitude, cost, and technology knowledge significantly affected behavioral intention. Self-efficacy, perceived ease of use, and perceived usefulness affected the attitude towards AI. Attitude mediated the relationship between perceived ease of use and behavioral intention as well as the relationship between perceived usefulness and behavioral intention. This study contributes to enhancing AI's understanding of the tourism and hospitality industry context. This study also improves TAM by proposing a comprehensive model with cognitive external and technology-specific factors.

KEYWORDS

Artificial Intelligence, Self-Efficacy, Subjective Norms, Technological Factors, Technology Acceptance Model, Tourism and Hospitality Companies

INTRODUCTION

Artificial Intelligence (AI) is a part of the industrial revolution 4.0, and the progress of AI is vast and grows very fast. The development of AI is significantly affecting the association with employees, customers, and other parties (Belanche et al., 2019). AI is immensely adding empathetic, intuitive, and analytical skills, allowing interacting as a new format that would be possible to adopt in business

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strategy (Huang and Rust 2018). This technology motivates the automation of services and processes, resulting in interacting directly with customers in frontline services (Van Doorn et al., 2017). Adopting AI can reduce the cost and time, eliminate human mistakes, and perform tasks quickly at any time within 24 hours. AI can also help with different tasks such as calculations, data analysis, and problem-solving, adding value to the hotel management. Travel and tourism businesses build a reputation by providing excellent customer service. In contrast, AI technology can support this in a variety of different ways: such as in the absence of staff, AI can provide fast response, tailor recommendations, and improve personalization.

Nowadays, some tourism, leisure, and hospitality companies are starting to accept AI in their firm. For example, AI and autonomous robots are being used to greet customers, serve meals, and cook, take orders already existing around the world (Osawa et al., 2017). According to Van Doorn et al. (2017), automation of services might have a considerable impact on customer behaviors and choices. Having a conversation like humans, intelligent digital assistants, and chatbots is increasingly used for customer services, marketing, and sales. The new version of AI-power bots is very much sophisticated and can be more potent in the future (Srinivasan, Nguyen & Tanguturi, 2019). Thereby, AI can ensure numerous new possibilities (i.e., vehicles and drones, autonomous robots; conversational systems such as digital assistants and chatbots; blockchain and machine learning) to transform hospitality, leisure, and tourism sectors obviously with a greater return.

This research identifies a few research gaps to be addressed. Tourists search for information to get a tourism destination via advanced technology. In response, tourism companies integrate those technologies to attract clients to their business. Although AI is a buzz issue, a few studies uncover the factors influencing intention to use AI-powered service robots (Nam et al. 2021; Zhong et al., 2020), Chatbots (Melián-González et al., 2019; Pillai & Sivathanu, 2020) in the tourism industry. Few other empirical studies on adoption concentrated on virtual reality (Choi et al., 2020; Lee et al. 2020; Li & Chen, 2019), augmented reality technology (Chung et al., 2015). Still, there is a dearth of comprehensive empirical research on the intention to use AI, which can explain the adoption reasons from technological, cognitive, and external forces for hospitality, leisure, and tourism industries. This is particularly in the context of Malaysia, which is an emerging tourist destination.

Thereby the objective of this paper is to identify the determinants of behavioral intention to adopt artificial intelligence powered online service. The present study will fill the literature gap in the adoption of AI technology in the Malaysian context. It contributes theoretically by offering an extension of TAM, incorporating a few cognitive factors in the proposed conceptual model. Beyond the usual relationship, this study experimented with mediating relationships to understand the reasons for adoption deeply in its empirical investigation. The new scale proposed will be a foundation for future research in their replication in similar AI technology fields.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

Technology Acceptance Model

Acceptance of artificial intelligence is considered as the information and communication technology adoption. The Technology Acceptance Model (TAM) is the most widely used information system research in the organizational context (Gangwar et al., 2014). The TAM explains how individuals and firms adopt new technology (Davis, 1986). The model proposes three constructs including attitude toward the system, perceived ease of use (PEOU) and perceived usefulness (PU) to explain the user motivation to adopt a new technology. Davis et al. (1989) included behavioral intention (BI) in TAM as a new construct directly affected by attitude and perceived usefulness. The TAM has been used by several researchers (Caniels et al., 2015; Rahayu & Day, 2015) in a variety of fields, including hospitality industries (Bhatiasevi & Yoopetch, 2015; Huang & Rust, 2018; Chung et al., 2015; Pillai & Sivathanu, 2020). This study will extend the TAM to examine the factors affecting the adoption of

AI powered customer services in the tourism and hospitality industry. Figure 1 shows the conceptual model of the study.

Perceived Ease of Use (PEOU)

Perceived ease of use is how the consumers perceive new services or products to be superior to their substitutes. Adopting new technology towards its usefulness depends on perceived ease of use (Bhatiasevi & Yoopetch, 2015). Likewise, Chung et al. (2015) found that perceived ease of use has a significant positive effect on attitude toward heritage sites. Users find technology easy to use when they identify that the technology can be used without difficulties. Therefore, the users use that technology regularly. Over the previous few decades, numerous researchers such as (Kamal et al., 2020; Bhatiasevi & Yoopetch, 2015) stated that perceived ease of use has a significant direct or indirect positive effect on usage intention. Huang and Rust (2018) have found that tourists are positively associated with analyzing the 3D tourist environment with their plan to visit. Therefore, the following hypotheses are proposed:

H1: There is a positive relationship between perceived ease of use and perceived usefulness of AI.
H2: There is a positive relationship between perceived ease of use and attitude towards AI use.
H3: There is a positive relationship between perceived ease of use and behavioral intention to use AI powered online service.

Perceived Usefulness (PU)

Perceived usefulness refers to the degree to which a person believes that using a particular system would enhance their job performance (Davis, 1989). When users perceived that information communication technology is beneficial to their business, this positive perception motivates them, and then they are intended to adopt information communication technology. Scholars found that this was positively linked to the desire of tourists to use consumer-generated media for travel planning (Ayeh et al., 2013) and their intention to shop for mobile social tourism (Hew et al., 2018) and virtual reality (Fagan et al., 2012). Scholars (Bhatiasevi & Yoopetch 2015; Casaló et al., 2010) have observed that a business-hosted online travel community's perceived utility was directly linked to the intention of customers to use the goods of the host company. The study of Chung et al. (2015) confirmed

Figure 1. Conceptual model

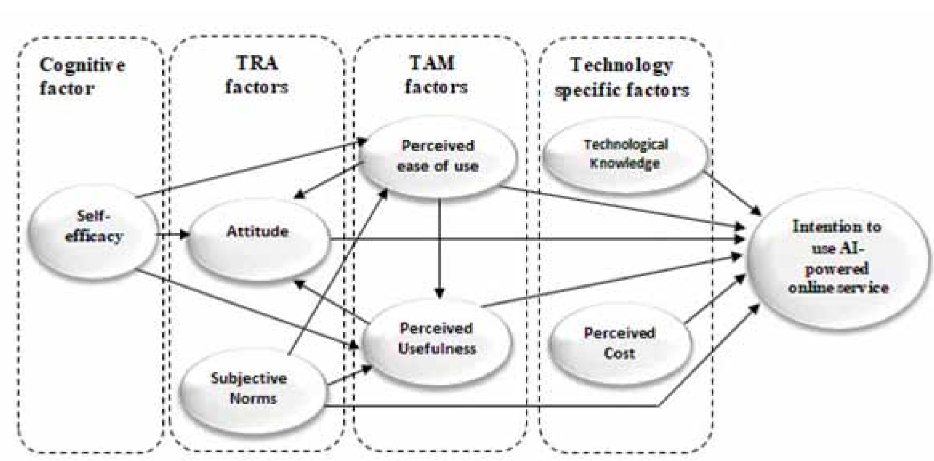


Figure 1: Conceptual Model

that perceived usefulness has a significant favorable influence on attitude. Therefore, the following hypotheses are proposed:

H4: There is a positive relationship between perceived usefulness and attitude towards AI use.
H5: There is a positive relationship between perceived usefulness and behavioral intention to use AI powered online service.

Attitude (Att)

Attitude is the favourable or unfavourable mindset that significantly influences behavioral intention (Ajzen 1991). Lee *et al.* (2020) conducted a study in the USA and confirmed that attitude has a significant positive effect on augmented reality technology's behavioral intention in the hospitality industry. Numerous studies in the hospitality industry have shown a significant positive relationship between attitude and buying intention (Kim and Qu 2014; Cha, 2020). As per Choi et al. (2020), avatars positively influenced their intended use and clarified how avatars affect intended use. Thus, the following hypothesis is proposed:

H6: There is a positive relationship between attitude and behavioral intention to use AI powered online service.

Need for Extending TAM

Although TAM is commonly used in almost all information system research, some limitations have been encountered. According to Wu (2011), TAM contains some restricted factors, which sometimes cannot properly handle new solutions or services. Garaca (2011) stated a limited possibility of prediction and explanation and a lack of practical value. Other researchers opined that an empirical study using TAM does not produce clear or consistent results; thus, it is important to identify additional constructs in the model (Legris et al., 2003). Since TAM explains between 30% to 40% of system use (Legris et al., 2003), the researcher Tarhini et al. (2017) argued that additional constructs with TAM might increase the explanatory power. This justification indicates the importance of the extension of the TAM model with other context-specific constructs. The followings are included as additional constructs in the study.

Self-Efficacy

Self-efficacy was a part of the social cognitive theory (Bandura, 1977) that is the individual's belief about their motivation and ability to perform specific tasks. Later, Compeau and Higgins (1995) adapted this definition in the technology adoption context and defined it as assessing one's own ability to use information technology (Pramana, 2018). To take technology into practice, only intended to use is not enough; a perceived capability is equally important to complete it. Compeau and Higgins (1995) study that self-efficacy significantly influences perceived ease of use and perceived usefulness, while others identified the relationship of self-efficacy with attitude (Budu et al., 2018; Gangadharbatla, 2020). Studies show that self-efficacy significantly affect the adoption and acceptance of IT (Igbaria, 1995). In this study, we assumed that the owner/manager's self-efficacy plays a vital role in the adoption intention of AI (Nuryyev et al., 2020). Therefore, the following hypotheses are proposed:

H7: There is a positive relationship between self-efficacy and perceived ease of use of AI.
H8: There is a positive relationship between self-efficacy and perceived usefulness of AI.
H9: There is a positive relationship between self-efficacy and attitude towards AI use.

Theory of Reasoned Action (TRA)

TRA was introduced by Fishbein and Ajzen (1975) to forecast human actions under the full volitional influence (i.e., based on conscious individual choice than the external forces). As per the theory, intention—the individual's state of readiness to participate in a specific activity—signals an individual's susceptibility to engage in that behavior (Ajzen, 1985). TRA analysis has two primary constructs: attitude and subjective norms.

The outcome of subjective norms (SN) on users' decision to use innovation was proved by Watjatrakul (2013). Some studies indicate a significant association about the lack of studies regarding the relations of SN on PEOU (Baki et al., 2018). The Schepers and Wetzels meta-analysis put some light on the effects of SN on TAM. They find that 91.67% of papers concerning the connection of SN to PU are significant. In 66.67% of articles that measure the impact of SN on PEOU, it is considered important. Some experiments suggest a significant association, although others indicate no significant relations between them. Though the negative findings sound negligible, most studies reveal the connection between SN and PU and PEOU. A social influence analogous to subjective norms is significantly related to the willingness to use AI-powered service robots in the tourism and hospitality business among the USA's undergraduate students (Lu et al., 2019). Therefore, the following hypotheses are proposed:

H10: There is a positive relationship between subjective norms and perceived ease of use of AI.
H11: There is a positive relationship between subjective norms and perceived usefulness of AI.
H12: There is a positive relationship between subjective norms and behavioral intention to use AI powered online service.

Technology Specific Factors

Perceived Cost

Cost is one of the most critical factors affecting technology adoption (Alam et al., 2011; Mochoge, 2014). The cost of developing a program for AI, maintenance, and upgrade web site and availing the services to the consumers are the main cost incur for web-based activities (Luarn & Lin, 2005). According to Hayes Jr. (2012), high cost is involved in technology implementation. Thus, small businesses are reluctant to use IT-based program. Although increased cost is involved in implementing IT, firms without the latest technology go far behind their competitors in this digital era. Therefore, the following hypothesis is proposed:

H13: There is a negative relationship between perceived cost and behavioral intention to use AI powered online service.

Technological Knowledge

Researchers identified a lack of expertise as the main factor hindering the adoption and diffusion of information technology (Crook & Kumar, 1998). When a company adopts new technology, the company usually goes through knowledge gain approaches before making a final decision and finding alternatives. Walczuch et al. (2000) found unfamiliarity with the Internet, Vassilopoulou et al. (1999) identify limited knowledge of how the internet helps organizational strategy hinders information technology adoption. Knowledge discovery is crucial as it will create awareness of identifying opportunities and the barriers and challenges faced during the adoption process. Once decision-makers have gained knowledge about the new technology, it will add value to adopting the latest technology. As a result, the following hypothesis is proposed:

H14: There is a positive relationship between technological knowledge and behavioral intention to use AI powered online service.

Mediating Effect of Attitude

Venkatesh et al. (2003) argued that attitude mediates the relationship between perceived usefulness and behavioral intention. Gajanayake et al. (2014) found that attitude partially mediates the relationship between perceived usefulness and behavioral intention. Krishanan et al. (2016) highlighted that attitude mediates the relationship between perceived ease of use, perceived usefulness, and behavioral intention. Therefore, the following hypotheses are proposed:

H15: Attitude mediate the relationship between perceived ease of use and behavioral intention to use AI powered online service.
H16: Attitude mediate the relationship between perceived usefulness and behavioral intention to use AI powered online service.

RESEARCH METHODS

Samples

A cross-sectional survey method was used to collect data from 336 respondents from Malaysia's hospitality and tourism companies. For sample size sufficiency, the current study used the G*power program (Faul et al. 2009). According to sets proposed by Cohen (1988) and for seven independent constructs or predictors, the suggested sample size was 153 (f2=0.15 for effect size, α=.05 for error type 1, and ß=0.20 for error type 2). Due to the inadequate information about the hospitality and tourism companies, those have greater internet usage; this study used the judgmental sampling method. The respondents for this study were the owner or managers of hospitality and tourism companies. Data were collected personally. At the time of data collection, we talked to the researchers' owner/manager and asked whether they were familiar with the term AI or experienced this technology. In this, only the respondents who are familiar with this technology were considered for the final survey. An Online-based survey was used in this study to confirm the respondents' anonymity and increase the number of responses (Richman et al., 1999). To reduce missing responses, an online questionnaire was developed in a way that respondents have to answer all questions. The majority of the respondents were male (84.2%) and ages in between 31-40 years (49.8%) as well as 41-50 years (34%).

Measurements

All the constructs of this study were operationalized as a reflective construct. The constructs and items were adapted, developed, collected from various past studies (see Appendix) to suit this research. The variables of this study were measured by using a 5-point Likert scale ranging from 1= strongly disagree to 5 = strongly agree.

As suggested by Harman (1960), we tested a common method bias employing exploratory factor analysis. Assessing sampling adequacy for factor analysis KMO (Kaiser-Meyer-Olkin) was used, and the results show that all the value was above 0.5 in the diagonal of the matrix and the KMO coefficient value was 0.843 that met the criteria (Malhotra, 1999). Secondly, assessing the numbers of factors appear in a model screen test and Kaiser-Guttman criterion was applied. The test results revealed 67.662 variances for seven factors with eigenvalues more than one, 32.4% variance explained by the first factor (Hair et al., 1998). Finally, the common method bias was tested by adding a marker variable based on Podsakoff et al.'s (2003) suggestion. The average variance explained less than 1% with a common factor with each item and the marker variable. Thus, we can conclude that common method bias was not an issue.

ANALYSIS OF THE DATA

IBM AMOS software version 21 and SPSS 25 was used to analyze the data. Variance based SEM (structural equation modeling) technique was employed in the present study to test the hypotheses. Two-phase appraisals of models: confirmative factors analysis (to determine the reliability and validity of items and factors) and structural model (which evaluate the model fitness and path analysis) were used following the guidance of Anderson and Ginberg (1988).

Measurement Model Evaluation

In the measurement model, the internal reliability (consistency), convergent, and discriminant validity of the factor were investigated, as shown in Table 1. Construct reliability has been inspected with Cronbach's alpha, composite reliability and rho, which are 0.711 to 0.914, 0.850 to 0.946, and 0.741

Table 1. Factor loadings, reliability and multicollinearity statistics

Constructs	Items	Loadings	α	CR	AVE	rho_A	VIF			
							Att	BI	PEOU	PU
Attitude (Att)	att1	0.904	0.914	0.946	0.853	0.920		1.917		
	att2	0.935								
	att3	0.932								
Behavioral intention (BI)	bi1	0.933	0.871	0.921	0.795	0.878				
	bi2	0.902								
	bi3	0.839								
Perceived cost (PC)	pc1	0.956	0.798	0.850	0.659	0.810		1.367		
	pc2	0.800								
	pc3	0.751								
Perceived ease of use (PEOU)	peou1	0.771	0.802	0.870	0.629	0.834	1.533	1.475		1.374
	peou2	0.850								
	peou3	0.882								
	peou4	0.752								
Subjective norms (SN)	sn1	0.724	0.778	0.853	0.594	0.796	1.597		1.249	1.298
	sn2	0.804								
	sn3	0.852								
	sn4	0.794								
Perceived usefulness (PU)	pu1	0.828	0.880	0.917	0.736	0.888	2.042	2.207		
	pu2	0.900								
	pu3	0.905								
	pu4	0.794								
Self-efficacy (SE)	se1	0.776	0.775	0.868	0.688	0.798	1.597		1.249	1.479
	se2	0.843								
	se3	0.866								
Technological knowledge (TK)	tk1	0.910	0.711	0.872	0.773	0.741		1.606		
	tk2	0.847								
	tk3	0.942								

CR= Composite Reliability, AVE= Average Variance Explained, VIF= variance inflation factor to 1.150 in this study. The results comply with the threshold value of 0.7 accordingly (Hair Jr. et al. 2016). Convergent validity was tested by extracting factor item loads and average variance extracted (AVE), which are 0.594 to 0.853 and 0.724 to 0.956 in this study. The results satisfy the standard of 0.5 and 0.7 respectively (Hair Jr. et al. 2016).

To conform with the general linear model's assumption before implementing the measurement model, data is screened for outliers and normality. To evaluate the outliers, the distance value of Cook was determined. Provided Steven's (1992) recommendation that responses with a Cook value above 1 should be omitted; the final analysis removed a total of 7 outliers. As far as normality is concerned, Table 2 shows that the data was average as the deviation from normality was not severe. The value of skewness and kurtosis was less than ±3 and ±10 (Kline, 2011).

The constructs' discriminant validity was assessed using the Fornell-Larcker criterion analysis and Heterotrait-Monotraits ratio (HTMT). According to the Fornell-Larcker approach (Fornell & Larcker, 1981), to determine the discriminant validity of a construct, the square root of each construct AVE value should be greater than its highest correlation with any other constructs of a model. This is consistent with this study, as shown in Table 2. Likewise, the Heterotrait-Monotraits ratio (HTMT), which is compatible with the disattenuated construct score, is a measure of the correlation between the constructs. Table 3 shows that no discriminant validity problem exists in the study (Henseler et al., 2015) based on the threshold value of 0.9.The results indicate that reliability and validity are adequate in the study.

Testing Multicollinearity and Coefficient of Determination

As suggested by Kleinbaum et al. (1988), one effective technique includes evaluating the Variance Inflation Factor (VIF) was used to decide the presence of multicollinearity among independent variables in this research. As shown in Table 1, the regression outcome reveals that the VIF ranged from 1.249 to 2.207, which indicated in between 1 to 5 (Zuur et al. 2010), which concludes that multicollinearity is not the issue of this research.

Santosa et al. (2005) proposed to measure the explanatory powers of the model by ascertaining the endogenous variable coefficient of determination (R^2). The value anything greater than 0.26 is

Table 2. Fornell-Larcker correlation matrix and normality data

	Att	BI	PC	PEOU	PI	PU	SE	TK
Att	**0.924**							
BI	0.656**	**0.892**						
PC	0.462**	0.314**	**0.812**					
PEOU	0.467**	0.541**	0.255**	**0.793**				
PI	0.503**	0.573**	0.500**	0.372**	**0.771**			
PU	0.634**	0.706**	0.438**	0.540**	0.594**	**0.858**		
SE	0.575**	0.670**	0.344**	0.494**	0.446**	0.549**	**0.829**	
TK	0.501**	0.551**	0.403**	0.383**	0.348**	0.570**	0.474**	**0.879**
Mean	3.342	3.298	3.413	3.475	3.441	3.358	3.074	3.258
Std. Dev.	0.812	0.828	1.089	0.754	0.718	0.869	0.752	0.733
Skewness	-0.485	-0.300	-0.620	-0.528	-0.465	-0.186	-0.297	0.157
Kurtosis	0.309	-0.375	-0.652	0.394	0.669	-0.151	-0.473	-0.531

Note: The bold diagonal values represent the square root of AVE; ATT= attitude; BI=behavioral Intention; PC= perceived cost; PEOU=perceived ease of use; PI=personal innovativeness; PU=perceived usefulness; SE=self efficacy; TK=technological knowledge. **. Correlation is significant at the 0.01 level (2-tailed).

Table 3. Heterotrait-Monotrait (HTMT) analysis results

	Att	BI	PC	PEOU	PI	PU	SE	TK	R^2	
									Value	Strength
Att	-								0.81	Strong
BI	0.732	-							0.86	Strong
PC	0.460	0.259	-							
PEOU	0.546	0.637	0.253	-					0.67	Strong
PI	0.554	0.663	0.588	0.424	-					
PU	0.704	0.797	0.398	0.615	0.684	-			0.74	Strong
SE	0.674	0.815	0.368	0.605	0.551	0.652	-			
TK	0.613	0.693	0.406	0.489	0.412	0.720	0.632	-		

stronger, less than 0.13 is weaker, and in between these ranges is deemed as moderate (Cohen, 1988). As shown in table 3, every endogenous value found in this research is over the prerequisites in the analysis, which indicates that the model has strong explanatory power (Falk & Miller, 1992).

Confirmatory Factor Analysis

After Fulfilling the measurement of reliability and validity, open up the way for the measurement model. In the measurement model, we assessed the confirmation of factors using confirmatory factor analysis (CFA). Table 4 shows that the resulting CFA model produced good fit indices: $\chi 2$=820.320, degrees of freedom (df)=296, Goodness of Fit Index (GFI)= 0.925, Tucker-Lewis Index (TLI)=0.912, IFI= 0.926, comparative fit index (CFI)=0.926, NFI=0.915, root mean square error of approximation (RMSEA)=0.073. The t-values corresponding to all the items was significant at less than 5%.

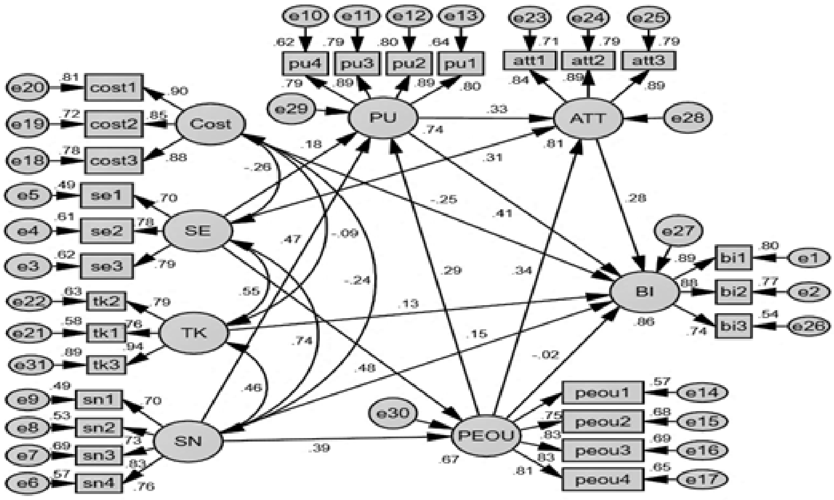
Structural Model

Figure 2 represents the structural model of this study. Since the measurement successfully has passed the CFA test in the measurement model, the structural model assessment tested the

Table 4. Results of CFA and structural model with standards

Fit indices	Measurement values for CFA	Meas. values for Structural Model	Standards with Sources	
$\chi 2$	820.320	877.358		
$\chi 2$/df	2.771	2.909	<3	Holbert & Stephenson (2002)
IFI	0.926	0.918	>0.900	Bentler & Bonett (1980)
NFI	0.915	0.905	>0.900	Bentler & Bonett (1980)
CFI	0.926	0.915	>0.900	Jöreskog & Sörbom (1993)
GFI	0.925	0.920	>0.900	Bentler & Bonett (1980)
AGFI	0.911	0.901	>0.900	Fornell & Larcker (1981)
TLI	0.912	0.90	≥0.90	McDonald & Ho (2002)
SRMR	0.045	0.052	<0.080	Bentler & Bonett (1980)
RMSEA	0.073	0.075	<0.080	McDonald & Ho (2002), Bagozzi & Yi (1988)

Figure 2. Structural Model



goodness of fit indices of the proposed model. The outcome of SEM represent that the conceptual framework showed a well data fit ($\chi2$ = 877.358, $\chi2$/df =2.909, GFI = 0.920, TLI = 0.901, CFI = 0.930, IFI = 0.918, RMSEA = 0.075). The realized value of Root Mean Square Error Approximation (RMSEA) was 0.075 that justifies the cut-off value less than 0.08 (Browne & Cudeck, 1993). As shown in Table 4, the other fit indices like CFI, GFI, IFI, TLI met the standard of close to 0.9 and higher (Bagozzi & Yi, 1988).

The structural model and the hypotheses of this research have been evaluated by using path coefficient based on the recommendation of Hair Jr. et al. (2016). It used 5,000 bootstrap subsamples from 209 cases to analyze the significance of the findings. The outcome shown in Table 5 indicates that there were statistically significant and positive relationships between perceived usefulness (β=0.411, t-value= 5.026, $p<0.01$), Attitude (β=0.272, t=3.378, $p<0.01$); Subjective norms (β=0.182, t=2.092, $p<0.01$), perceived cost (β=-0.179, t=-7.514, $p<0.01$), TK (β=0.146, t=3.504, $p<0.01$) and behavioral intention of consumers except perceived ease of use (β=-0.023, t=-0.272, $p>0.05$). The other relationship between perceived ease of use (β=0.322, t=3.547, $p<0.01$), SE (β=0.198, t=2.244, $p<0.05$), Subjective norms (β=0.555, t=5.826, $p<0.05$) and PU become significant. Likewise, perceived usefulness (β=0.337, t=4.844, $p<0.01$), Self-efficacy (β=0.341, t= 4.123, $p<0.01$) are found to have related with Attitude. However, self-efficacy (β=0.463, t=5.647, $p<0.01$) and subjective norms (β=0.417, t=4.750, $p<0.01$) are significantly related to perceived ease of use. Therefore, the research hypotheses *H1*, *H2*, *H4~H14* are supported; but the research hypothesis *H3* is not supported.

Mediation Test

We used bootstrapping approaches to test the mediation effect of attitude and adoption intention of AI technology as suggested by Hayes and Preacher (2010) and Hair et al. (2016). Since the distribution is normal, we used a bootstrapping approach instead of the Sobel test. The joint significance of the indirect effects method is the proper analysis, which can provide the needful endorsement. Fritz et al. (2012) have strongly urged that researchers use this test in conjunction with other tests.

As shown in Table 5, attitude fully mediated the relationship between perceived ease of use and behavioral intention as the direct relation turned insignificant (β=.847, p>.05) and the indirect relation became significant (β=0.009, $p<0.001$) after including attitude as mediating variable. Besides, attitude also mediated the relationship between perceived usefulness and behavioral intention, since

Table 5. Structural model and hypothesis testing Result

Hypothesis	STD Beta	STD Error	*t*-Values	*P*-Values	Significance (p<0.05)
H1: PEOU -> PU	0.322	0.091	3.547***	0.000	Supported
H2: PEOU -> ATT	0.389	0.087	4.459***	0.000	Supported
H3: PEOU -> BI	-0.023	0.084	-0.272	0.786	Not Supported
H4: PU -> ATT	0.337	0.070	4.844**	0.000	Supported
H5: PU -> BI	0.411	0.082	5.026***	0.000	Supported
H6: ATT -> BI	0.272	0.081	3.378***	0.000	Supported
H7: SE -> PEOU	0.463	0.082	5.647***	0.000	Supported
H8: SE -> PU	0.198	0.088	2.244**	0.025	Supported
H9: SE -> ATT	0.341	0.083	4.123***	0.000	Supported
H10: SN -> PEOU	0.417	0.088	4.750***	0.000	Supported
H11: SN -> PU	0.555	0.095	5.826***	0.000	Supported
H12: SN -> BI	0.182	0.087	2.092***	0.000	Supported
H13: PC -> BI	-0.179	0.024	-7.514***	0.000	Supported
H14: TK -> BI	0.146	0.042	3.504***	0.000	Supported
H15: PEOU->Attitude->BI	0.009	0.00	***	0.000	Full Mediation
H16: PU->Attitude->BI	0.010	0.00	***	0.000	Partial Mediation

Note: SE= Self-efficacy, PEOU= Perceived Ease of Use, PU= Perceived Usefulness, ATT= Attitude, SN= Subjective Norms, PC = Perceived Cost, TK = Technological Knowledge, BI= Behavioral Intention. *** significant at the 0.01 level (2-tailed). ** significant at the 0.05 level (2-tailed).

the direct (β=.026; p<.001) and indirect (β=.010; p<.001) relations became significant and the direct effect became lower after the inclusion of attitude as mediator. Therefore, research hypotheses *H15* and *H16* are supported.

DISCUSSIONS

In this research, we extended TAM with eight constructs, and all of them are tested empirically. Notably, in the current extended model, the R^2 values of usage intention are 0.86, which is much greater than the values of 0.40 observed in the earlier TAM model (Sun & Zhang, 2006; Ventakatesh et al., 2003). Even this explanatory power is greater than the previously extended TAM studies for the dependent variable of behavioral intention (Otter & Beer, 2020; Zheng & Li, 2020). These results showed that as extended TAM can predict behavioral intention, the proposed model is generally comprehensive, adequate, accurate, and functional for understanding AI in the tourism sector.

As hypothesized *H7*, *H8* and *H9* are supported, self-efficacy is a vital predictor that affects attitude, perceived ease of use and perceived usefulness. The present study confirms that owners/managers perceived that their effort, perseverance, and anxiety are related to adopting AI in their business, which is in line with the prior studies (Lew et al. 2020). Self-efficacy as a predictor of perceived ease of use is consistent with the past studies (Venkatesh et al. 2003); but self-efficacy as a predictor of perceived usefulness is inconsistent with the study of Rezaei et al. (2020). To adopt AI powered on-line service, it requires much effort from the owner/manager and persistence in accepting this technology in difficult situation to achieve its success. Owner/manager of a tourism and hospitality businesse with greater self-efficacy on AI has demonstrated a positive attitude towards AI technology adoption, which complies with the study of Gangadharbatla (2020).

Confirming hypotheses *H10*, *H11* and *H12*, this study also found that subjective norms are another crucial predictor influencing perceived ease of use, perceived usefulness, and behavioral intention. The outcome supports Lu et al. (2019) who found the significance of social influence but relatively lower influence for hotels than the retail stores in service robots. He commented that social norms influence greatly when referents influence is higher to him/her or limited knowledge of user on the technology. Therefore, individuals with greater subjective norms would accept AI technology in their business. This signifies that higher subjective norms lead to higher perceived ease of use, perceived usefulness, and behavioral intention.

In compliance with hypotheses *H4* and *H5*, this study shows that perceived usefulness has a significant effect on attitude and behavioral intention. Perceived usefulness is the most influential factor predicting adoption intention, similar to past studies (Hew et al., 2018; Li & Chen, 2019). Artificial intelligence can help businesses save money and time to removing human error and provide the task to be performed immediately at any time because AI can perform the tasks that require human interaction. Hotel and tourism companies try to build up their reputation by providing excellent customer service, and AI technology can deliver this with varieties of different ways. One to one relationship is possible by using AI technology, and even without the staff, it provides faster response and given tailor recommendation. As Malaysia is a tropical country, many tourists visit Malaysia every year from different parts of the world, and there are time differences between Malaysia and other countries. The distant time horizon is not affecting the business of tourism companies.

As supported *H6*, the study endorses a significant association between attitude and behavioral intention. Previous studies (Choi et al., 2020; Kim & Qu, 2014; Lee et al., 2020) are consistent with this study results. Adoption of AI technology requires mental and physical effort. If the tourism companies' owner/manager does not have a positive attitude towards using it, it is impossible to adopt in the organization. This study result confirms that a positive attitude is another essential predictor for AI technology usage among Malaysia's tourism companies.

This study also confirmed that perceived ease of use does not significantly affect behavioral intention because *H3* was not supported, which is in opposite to the study of Li and Chen (2019) on travel intention. Owners/managers of travel businesses find that accepting AI technology would be possible if it does not require much effort. Endorsing the taken hypotheses 1 and 2, this study also reveals that perceived ease of use has a significant effect on perceived usefulness and attitude. This study's results align with the previous studies (Chung et al., 2015; Huang & Rust, 2018). Moreover, attitude mediates the relationship between perceived usefulness, perceived ease of use, and behavioral intention. These study results are consistent with the previous studies (Gajanayake et al., 2014; Krishanan et al., 2016). Thus, ease of use is not only a factor that develops their attitude towards technology adoption. Other factors are also important to make a positive attitude on specific technology adoption. As the respondents of this study are owner/managers of travel and tourism businesses those have an online presence, therefore they are familiar with the technology usage and positive attitude about it.

By accepting hypothesis *H13*, this study confirmed previous studies (Alam et al., 2011; Mochoge, 2014) that perceived cost is the most critical predictor of adopting AI technology. Developing systems and other appliances incur high costs. To manage the AI technology company needs an employee with technical skills. This incurs a higher cost for the organization. This study results confirmed that perceived cost negatively affect behavioral intention, while this contradicts the previous study by Otter and Beer (2020) that identified an indirect relationship with intention via perceived usefulness. These negative influences on AI adoption intention among tourism and leisure companies in Malaysia as the results have negative beta value.

Besides, AI technology will deploy successfully when the owner/manager has technological knowledge about it. AI technology knowledge is essential because it is a very new technology, which is still at the primary stage worldwide. Malaysia is one of the emerging countries where the travel and tourism sector contributes a large portion to its GDP. Therefore, companies with supportive technology can contact their tourist directly and possibly increase the number of visitors in this country. Elbeltagi and Sharji (2013) stated that if the owner/manager lacks knowledge about the specific technology adoption process and is not familiar, the potential benefits might be discouraged from adopting information technology. This research confirmed hypothesis *H14* and found that technology knowledge would significantly influence AI technology adoption intention.

CONCLUSION

The objective of the study was to identify the factors affecting the intention to use AI in the tourism and hospitality sector. The study developed an extended model where all the factors taken were found significant by the empirical research except the relationship between perceived ease of use and attitude. This study also confirms that perceived usefulness, ease of use, attitude, cost, and technology knowledge significantly affect behavioral intention. Self-efficacy, personal innovativeness, and perceived usefulness forms attitude towards AI use except perceived ease of use. Besides, attitude partially mediates perceived ease of use, perceived usefulness, and behavioral intention.

Theoretical Contribution

The contributions of this research are manifolds. First, this study has contributed to the tourism industry and its literature, especially for the online customer service to explain the reasons to use AI in its operation. It validated the previous findings in similar technology addressing existing constructs to predict usage intention in the Malaysian context. Second, from the theoretical context, it contributes significantly to TAM with successful extension attributing additional constructs both the cognitive (self-efficacy), external influence (subjective norms), technology-specific factors (technological knowledge, perceived cost) in AI adoption. The additional constructs are integrated from the TRA and social cognitive theory. Thus, it covers almost all the competing and popular models. Third, it also established attitudes as a mediator in the relationship between perceived ease of use and perceived usefulness and behavioral intention empirically.

Fourth, to measure each construct, a measurement instrument was developed to operationalize the conceptual model in this research applying the SEM method using sophisticated software AMOS, which can be replicated in a similar research context in the globe. Finally, this research covered the limitation of the original TAM in terms of its explanatory power. With the proposed constructs, the explanatory power reached 0.86%, much significant than even the contemporary research in a similar field. Thus, this study's main objective is to examine the factors that affect the intention to adopt AI in emerging countries' tourism and hospitality business.

Practical Implications

This study explains the implications of tourism management. The managers/owners need to develop a positive attitude to ensure acceptance of AI in their business. In this study, perceived ease of use and usefulness were significantly associated with behavioral intention, but the same thing does not always happen in a different context. Therefore, owners/managers of tourism businesses need to consider other contextual factors explained in this research. The concerned parties should follow the following implications:

Firstly, as technological knowledge is found as a significant factor for the intention to use AI in the tourism sector, the knowledge gap must be reduced to find the diffusion of this technology. If owners/managers of tourism businesses do not know about AI technology, they must go for training to further improve-their knowledge gain. Since this sector is auspicious for Malaysia, the Enhancement of the tourism and hospitality education (Sarkar & George, 2019) nationwide integrating the technology-related materials in the curriculum might bring a fruitful result in building a sense of benefits among business houses and consumers simultaneously. Moreover, owner/manager capabilities to adopt AI are necessary.

Secondly, the study revealed that perceived cost is a vital factor predicting the intention to use the AI in their business. Apparently, this new technology's adoption is a burden for the business house to accumulate significantly for the small and medium firms in the industry. Although the cost of installation and purchase of technology requires big money initially, for the owner/manager, this is their investment for a better return on investment. The cost could be manageable by owners if they can be motivated, shedding light on its benefits in minimizing possible human errors, attending tourists, improved customer relationship management, increased operational efficiency, and future productivity. The AI supporting organization should campaign vigorously with the help of the concerned ministry. Besides, policymakers should develop a bridging gap by direct funding to address the cost and make it accessible to all. They should concentrate on the comprehensive research on AI technology so that AI, Internet of Things, and consumer Tech companies can flourish domestically and reduce their operational costs.

Thirdly, creating a favorable climate, nurturing and introducing an AI-backed system in various sectors, especially in Malaysia's tourism sector, could be a game-changing effect. The Government can show the leading path by adopting AI in the Malaysia Tourism Promotion Board (MTPB) activities to attract others. Fourthly, during COVID19, the tourism and hospitality sectors suffered worldwide, and Malaysia is not the exception. The country has banned tourists outside, especially from China, which would not be necessary if a detection system for the COVID affected tourists. Recently, MYEG Services Bhd. developed a health-risk profile using a person's historical geo-location information and serving Malaysia and the Philippines (Reuters, 2020). The government should patronize such effort and employ policy to broaden this service in other sub-areas such as hotel travel and tourist sites relating to the tourism sector.

LIMITATION AND FUTURE DIRECTION

This research has some limitations that must be considered in future research in a similar context using the same constructs. The current study is conducted from a developing country perspective and got higher explanatory power. Therefore, there is a need to conduct further studies in other developing and developed countries using the proposed model to justify the result. Particularly, it can be replicated in other developing countries to verify whether the enhanced explanatory power is only an anomaly or due to the changes of context. This research is a cross-sectional study that took a one-time survey. Future investigations should conduct a longitudinal study using a timeframe.

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APPENDIX

Self-Efficacy (Chao, 2019)

- I am convinced that I will adopt AI in our business
- I could figure out a way to implement AI in our business
- I am confident of using AI even if I have never used it before

Subjective Norms (Aji et al., 2020)

- People whose opinions I value would prefer me to use AI application
- Most people who are important to me think I should use an AI application
- Most people who are important to me would want me to use an AI application
- Majority of people I know around use AI application

Perceived Ease of Use (Alam et al., 2018)

- I think using artificial intelligence application is easy
- I think it is effortless to learn how to use AI application
- I think it does not require much effort to use an AI application
- I think AI application is clear and understandable

Perceived Usefulness (Janssen, 2018)

- I can improve the business process with an AI application
- The business process will be more efficient with an AI application
- AI will be helpful while doing business
- AI will improve our ability while doing business

Attitude (Alam et al., 2018)

- I like the idea of doing business with AI
- I think that it is a good idea in doing business with AI
- I have a favorable attitude towards doing business with AI

Technological Knowledge (Authors' Proposition)

- I have a better understanding of AI application
- I have sufficient knowledge about how to handle AI application
- Overall, I know pretty well about the AI technology

Perceived Cost (Alam et al., 2011)

- The initial set up cost is high
- Incur extra cost for hiring IT staff
- Assessing cost and benefits is difficult

Intention to Use (Authors' Proposition)

- I will consider artificial intelligence while doing business
- I think it will be worth to use AI in our business
- Regularly, I will use AI in our business