Psychological Factors in Consumer Acceptance of Artificial Intelligence in Leisure Economy: A Structural Equation Model

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Abstract

In global economics, Artificial Intelligence (AI) developed rapidly along with mobile internet, big data and sensor network. Technology becomes a key segment of an innovation system that affects global tourism. To analyze the pattern of technology in tourism leisure economy is to determine the critical mechanism of the innovation network in global tourism. This paper examines the psychological factors affecting the adoption of AI in leisure economy by individual consumers. 560 valid Data was analyzed via structural equation modeling. Based on the study results, expected performance of AI, social circle, facilitating conditions, pleasure derived from using AI, price value, and user habit significantly influence AI adoption. And Personal Innovativeness is verified as a new factor in the integrated research model. This study contributes to the explanation of the determinants in AI acceptance and provides an insight for AI manufacturers or leisure industries to better understand consumer behaviors.

Keywords: User acceptance, Artificial intelligence, Tourism leisure economy, UTAUT2 model

1 Introduction

Artificial Intelligence (AI) is the ability for a machine to collect information and use sophisticated algorithms and logical functions to learn from it, thereby adapting future capabilities based on additional information to increase knowledge [1]. The great progress of science and technology has promoted the rapid development of Artificial Intelligence. Investment in advanced technology and new systems noticeably increased. Since 2013 to the first quarter of 2018, China attracted more than half of the investment in AI sector globally(60%), and by 2017 the AI market in China amounted to 333.5 billion US dollars, which recorded a y-o-y growth of 67% [2]. Servion also predicted that by 2025, AI will support 95% of service interaction in our daily life. In tourism industry, AI can recommend guests of popular activities and local restaurants. And research in the automatic speech recognition field is a major aspect of the AI development, which improves communication in global tourism. The era of AI is coming, redefining the way how human beings think and the rules of the world.

But there is a scarcity of research in the area of AI acceptance, specifically for leisure economy. One similar study was conducted to examine the determinants for the healthcare doctors to use artificial intelligence-based medical diagnosis support system (AIMDSS) [3]. However, that study was developed by using The Unified Theory of Acceptance and Use of Technology (UTAUT1), which only involved four constructs: Facilitating Conditions, Social Influences, Effort Expectancy and Performance Expectancy. In this paper, a more comprehensive approach will be adopted after theoretical review of UTAUT 2 theory in section 2. Hypotheses with a new construct: Personal Innovativeness will be developed in section 3 and Partial Least Squares regression was applied to test the proposed research model in section 4. Section 5 demonstrates the results and conclusion and limitation will be drawn in section 6 and 7 respectively. The current research will help provide insights regarding the acceptance of Artificial Intelligence (AI) and serve to enlighten those in innovative industry, specifically those working in the field of AI management and consumer behavior.

2 Theoretical Background

2.1 Prior Research on Technology Adoption

Substantially improvement was made by information technology [4-6]. But it was users' willingness to accept and use of these certain technology that made the differences [7-8]. Fishbein

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and Ajzen developed the Theory of Reasoned Action [9], which was based on social psychology, explained the relationships between attitudes, intentions and behaviors. And Ajzen and Fishbein extended it into Theory of Planned Behaviour. They found that attitude, subjective norm and perceived behavioral control influence behavior intention. Davis examined Perceived Usefulness and Perceived Ease of Use are two main determinants [10]. And Venkatesh et al. incorporated eight prominent technology acceptance theories into The Unified Theory of Acceptance and Use of Technology and had better prediction [11].

2.2 The Unified Theory of Acceptance and Use of Technology 2

This research is based on UTAUT2 theory. In UTAUT model, Social Influences, Performance Expectancy, Facilitating Conditions and Effort Expectancy are identified as key factors on user intention of using new technology. Recently, Venkatesh, Thong, & Xu developed UTAUT to UTAUT 2 model by adding three more constructs [12] (Figure 1). The UTAUT 2 model explains the adoption of a technology from the individual perspective while the previous UTAUT theory explains the determinants within the organization. As the purpose of this paper is to assess the determinants from individual consumers' view, the UTAUT 2 model will be adopted.

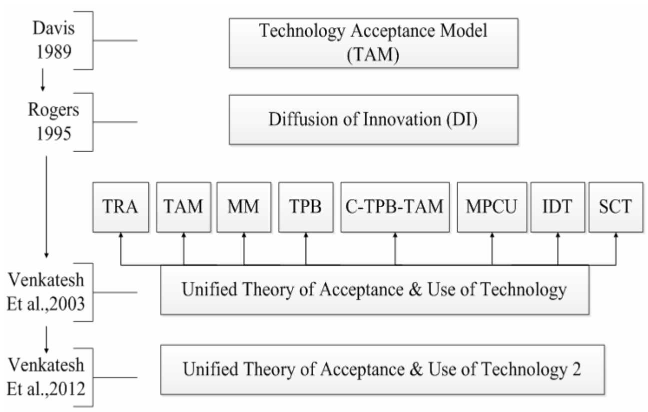

Figure 1. Literatures on technology adoption

3 Hypotheses

Prior research established the validity of the UTAUT2 survey as an effective means of quantitative data collection [12]. To guide this research, the main question under examination is: "What are the psychological factors influencing use of AI technology for individual consumers in leisure economy?". This study explored whether the primary factors of adoption identified in the UTAUT2 model may influence on BI toward using AI. Besides, Personal Innovativeness (PI) was integrated as a moderator in this study. Figure 2 shows the research model.

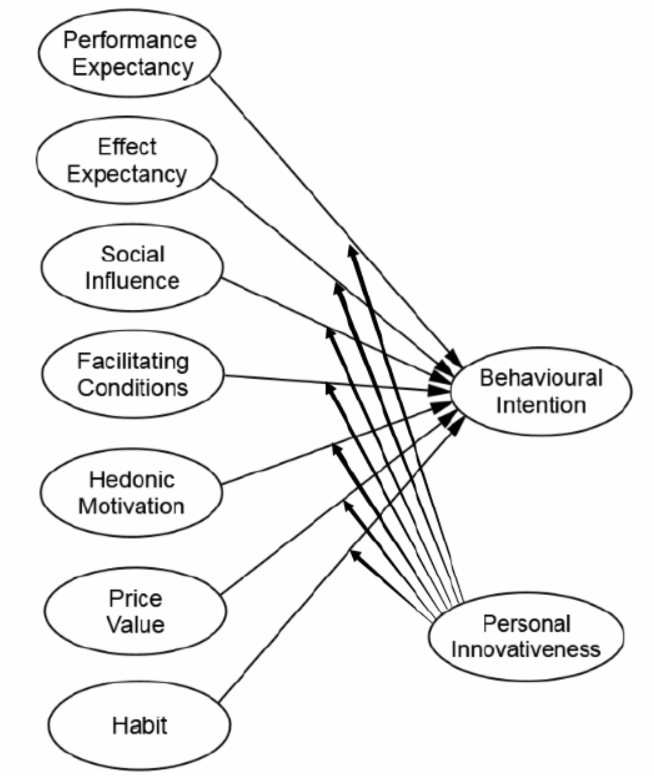

Figure 2. Research model

3.1 Performance Expectancy (PE)

PE is defined as the degree to which the use of AI will increase efficiency of leisure activities. The higher are the consumers' expectations of the AI service, the more likely they will use it.

H1: Consumers' PE significantly influences their Behavioral Intention(BI) to use AI in leisure economy

3.2 Effort Expectancy (EE)

EE is the user's expectation of convenience that is achieved by using the AI technology. It is assumed that consumers must feel that the AI service is easy to use, otherwise there would be less incentive to use them.

H2: Consumers' EE significantly influences their BI to use AI in leisure economy

3.3 Social Influence (SI)

SI is defined as the degree to which a consumer believes that their friends or parents, believe that it's good for the user to adopt AI technology. In cases in which many a user's friends are habitually using AI, this could lead to higher intention of use of that user.

H3: Consumers' SI significantly influences their BI to use AI in leisure economy

3.4 Facilitating Conditions (FC)

Facilitating conditions is defined as the degree to which the consumer believes that there are necessary support, whether organizational or technical can facilitate the use of AI, such as online instruction and continued support.

H4: FC significantly influences consumer's BI to use AI in leisure economy

3.5 Hedonic Motivation (HM)

HM is the pleasure derived from use of AI. AI users might find it pleasant during the use. Therefore, hedonic motivations may encourage consumers to use AI.

H5: HM significantly influences consumer's BI to use AI in leisure economy

3.6 Price Value (PV)

PV is the perceived benefit of adopting AI technology compared with its cost. Since many efficient companies usually have an AI layer service or support that understands and responds to most of the basic questions, consumers are willing to adopt AI service at a low cost.

H6: PV of AI significantly influences consumer's BI to use AI in leisure economy

3.7 Habit

Habit reflects the outcome of previous experiences. Once AI users have good experience when pursuing leisure activities, this experience will lead them to use AI more frequently.

H7: HB significantly influences consumer's BI to use AI in leisure economy

3.8 Personal Innovativeness (PI)

Midgley and Dowling defined Personal Innovativeness as the degree to which the consumer is receptive to new ideas, and they make innovation decisions independently. Huntley and Chacko concluded that Generation Y are highly educated and technologically savvy [13-14]. They believe that technology is integral to life [15]. People with personal innovativeness might have more willingness to use new technologies.

H8: PI moderates the effects of PE, EE, SI, FC, HM, PV and HB on BI to use AI in leisure economy

4 Method

4.1 Research Design

This research used an adapted version of the UTAUT2 instrument to evaluate. All constructs were measured using 3 or 4 items. And the items used to evaluate Personal Innovativeness were adopted from Agarwal et al.,. Since technology in tourism leisure economy is an active process of scientific output to user sectors and China is a developing country with uneven regional economic development, the investment in AI and its utilization varied in different districts. Thus, the questionnaire was designed to cover mainland China, Hong Kong, Macau and Taiwan. And mainland China was divided into seven large areas. The occupation category was classified into eight types according to the "The Occupational Classification of China". Eight constructs measured on a 7-point Likert scale. Table 1 illustrates the measurable items of eight constructs.

Table 1. Measurable items of eight constructs

	Measurable Items
PE1	I find AI useful in leisure activities
PE2	Using AI increases my efficiency of leisure activities
PE3	AI helps me accomplish leisure activities more quickly
PE4	AI increases my chances of achieving things that are important to me
EE1	I find AI easy to use in leisure activities
EE2	Learning how to use AI is easy for me
EE3	It is easy for me to become skillful at using AI
EE4	My interaction with AI is clear and understandable
SI1	My families suggests me to use AI
SI2	My friends think that I should use AI
SI3	People whose opinions that I value prefer that I use AI
FC1	I have the resources necessary to use AI
FC2	I have the knowledge necessary to use AI
FC3	AI are compatible with my other technologies
FC4	I can get help from others when having difficulties of using AI
HM1	Using Artificial Intelligence is fun for me
HM2	Using Artificial Intelligence is very enjoyable
HM3	Using Artificial Intelligenceis very entertaining
PV1	Artificial Intelligence is reasonably priced
PV2	Artificial Intelligence is a good value for the money
PV3	At current price, Artificial Intelligence provides a good value
HB1	Using Artificial Intelligence becomes a habit for me
HB2	I am addicted to using Artificial Intelligence
HB3	I must use Artificial Intelligence
HB4	Using Artificial Intelligence has become natural to me
BI1	I intend to continue using Artificial Intelligence
BI2	I will always try to use Artificial Intelligence in my studies
BI3	I plan to continue to use Artificial Intelligence frequently

4.2 Data Collection and Analysis

The target population was consumers who performed leisure activities engaging with AI technology. Online survey was posted from March to April on a popular questionnaire online platform in China (www.sojump.com) in 2019. At the end, 759 sets of data were collected. Since 199 sets of data are invalid due to incomplete information or improper input, the sample size narrowed down to 560 and the valid response rate was 73.8%. To examine common method bias, Harman's single factor test was applied via SPSS Statistics 26. Results revealed that there are six factors explaining 56.4% of the variance where the first factor accounted for 25.8%. Thus, common method variance is not a major validity issue here.

4.3 Partial Least Squares

As a second-generation structural equation modeling technique, Partial Least Squares regression can fit multiple response variables into one single model. And since it does not assure the predictors are fixed, it is more robust to measure uncertainty. Therefore, SmartPLS 3.2.8 was applied to test the proposed research model.

5 Results

5.1 Sample Characteristics

Among the respondents, 56.96% are males while 43.04% are females, and male respondents are 13.92% more than female. They have diversified occupations. Elite people like Technicians or Professionals used AI most (36.61%). And young generations aged 20-29 accounted more than 50%, followed by people aged 30-39(34.11%). People in economically developed districts (Southern China, 23.75% & Eastern China, 22.86%) experienced AI more often.

5.2 Reliability & Construct Validity

Anderson & Gerbing suggested the first step in PLS analysis is to evaluate the reliability and validity of each construct [16]. Table 2 presents the PLS Outer loadings. The PLS Outer loadings of all constructs in research model exceeded 0.7, reaching the recommended level.

Table 2. PLS outer loadings

	PLS Loadings
PE1	0.80
PE2	0.77
PE3	0.77
PE4	0.78
EE1	0.81
EE2	0.78
EE3	0.79
EE4	0.77
SI1	0.79
SI2	0.84
SI3	0.83
FC1	0.73
FC2	0.76
FC3	0.72
FC4	0.73
HM1	0.82
HM2	0.79
HM3	0.76
PV1	0.78
PV2	0.83
PV3	0.81

Table 2. PLS outer loadings (continue)

	PLS Loadings
HB1	0.78
HB2	0.80
HB3	0.80
HB4	0.79
PI1	0.71
PI2	0.86
PI3	0.87
BI1	0.78
BI2	0.81
BI3	0.84

Table 3 demonstrates that the Cronbachs' alpha, CR and AVE values of every constructs exceeded 0.7, 0.7 and 0.5, respectively, indicating a high degree of reliability and validity of the data.

Table 3. Cronbachs' alpha, CR, and AVE

	Cronbachs' Alpha	CR	AVE
Behavioral Intention	0.73	0.85	0.65
Effort expectancy	0.80	0.87	0.62
Facilitating Conditions	0.74	0.74	0.52
Hedonic Motivation	0.70	0.83	0.63
Habit	0.77	0.86	0.60
Performance expectancy	0.79	0.86	0.61
Personal Innovativeness	0.75	0.85	0.66
Price Value	0.73	0.85	0.65
Social Influence	0.76	0.86	0.67

Table 4 presents the correlation analysis of eight variables. Since the square root of each AVE is greater than its construct correlations, it indicates the data is relatively independent of one another.

Table 4. Square roots of AVEs

	BI	EE	FC	HB	HM	PE	PI	PV	SI
BI	0.81								
EE	0.28	0.79							
FC	0.49	0.41	0.65						
HB	0.47	0.31	0.47	0.77					
HM	0.39	0.26	0.31	0.30	0.79				
PE	0.55	0.24	0.38	0.30	0.36	0.78			
PI	0.48	0.25	0.36	0.42	0.34	0.34	0.81		
PV	0.42	0.24	0.42	0.55	0.31	0.33	0.31	0.81	
SI	0.46	0.26	0.38	0.47	0.28	0.45	0.27	0.34	0.82

Table 5 shows the Heterotrait-monotrait ratio of correlations (HTMT) of seven constructs and each value is less than 0.85, reinforcing the discriminant validity of the data.

5.3 Model Comparison

To compare the difference of adding Personal Innovativeness to UTAUT2 model to other metrics or the original model in the improvement of accuracy, we tested the research model 2 by adding income as a moderating factor.

Table 5. HTMT

	BI	EE	FC	HB	HM	PE	PI	PV
BI								
EE	0.35							
FC	0.76	0.64						
HB	0.62	0.38	0.70					
HM	0.53	0.34	0.50	0.41				
PE	0.73	0.30	0.58	0.38	0.47			
PI	0.63	0.33	0.55	0.58	0.44	0.43		
PV	0.57	0.30	0.69	0.73	0.44	0.43	0.42	
SI	0.62	0.32	0.57	0.62	0.38	0.59	0.36	0.47

Figure 3 and Figure 4 demonstrates the research model with moderating factor Income and its R^2 (0.483) of SmartPLS analysis. And Figure 5 presented the R^2 (0.512) of SmartPLS analysis with Personal Innovativeness and Figure 6 presents the R^2 (0.467) of SmartPLS analysis without Personal Innovativeness. The R^2 of the research model with PI is 0.512, meaning the UTAUT 2 model integrating Personal Innovativeness explained 51.2% of the variance in AI technology adoption, which is better than the other two without PI (46.7%) or with moderating factor Income (48.3%).

Figure 7 demonstrates the results of SmartPLS analysis. Bootstrapping was performed using 560 responses to 5000 samples.

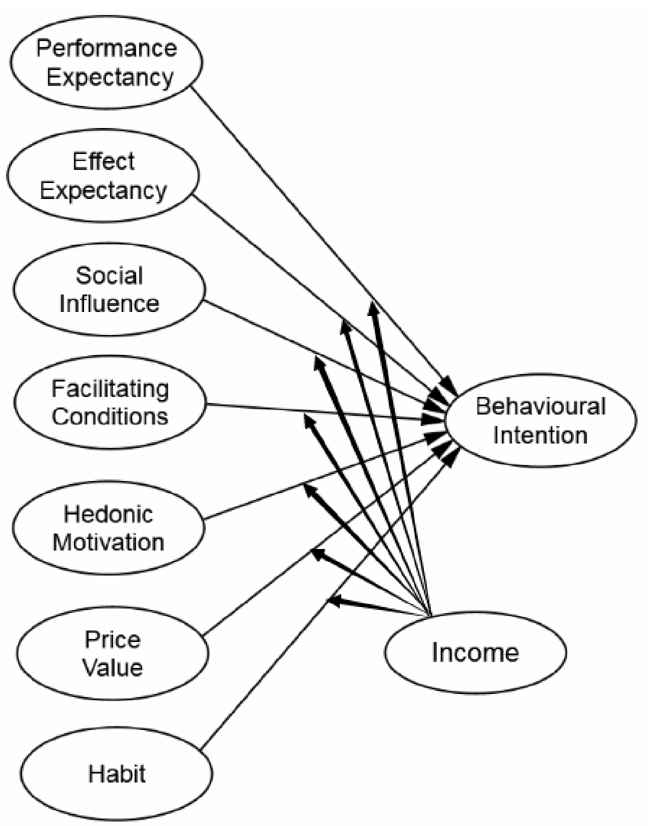

Figure 3. Research model 2: UTAUT2 model with income

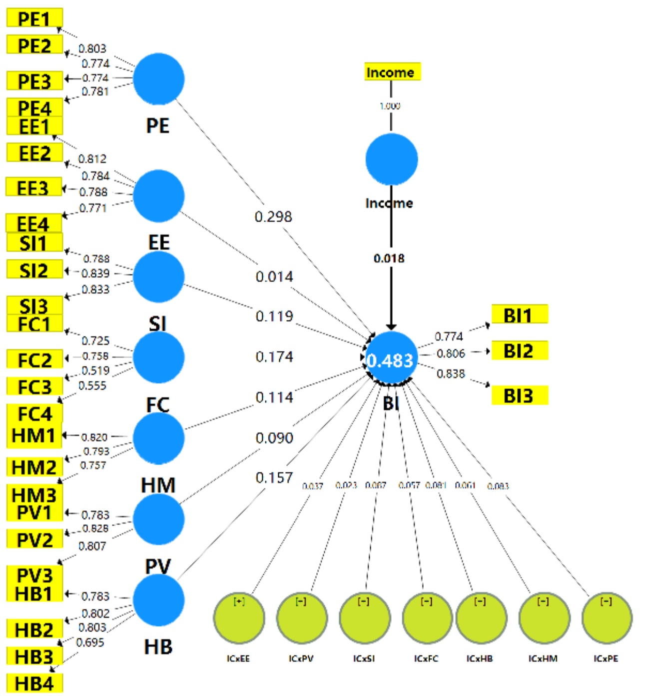

Figure 4. PLS analysis with income

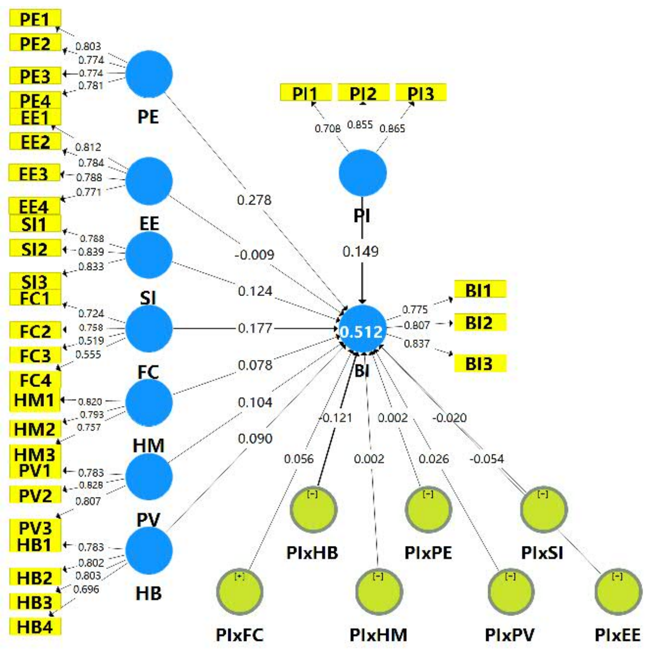

Figure 5. PLS analysis with PI

6 Conclusion

According to the SmartPLS results, the P-values of six constructs are less than 0.05, meaning PE, FC, SI, PV, HM and HB have significant influence on BI. Thus, except H2, all the other Hypothesis 1, 3, 4, 5, 6 and 7 are supported (Table 6).

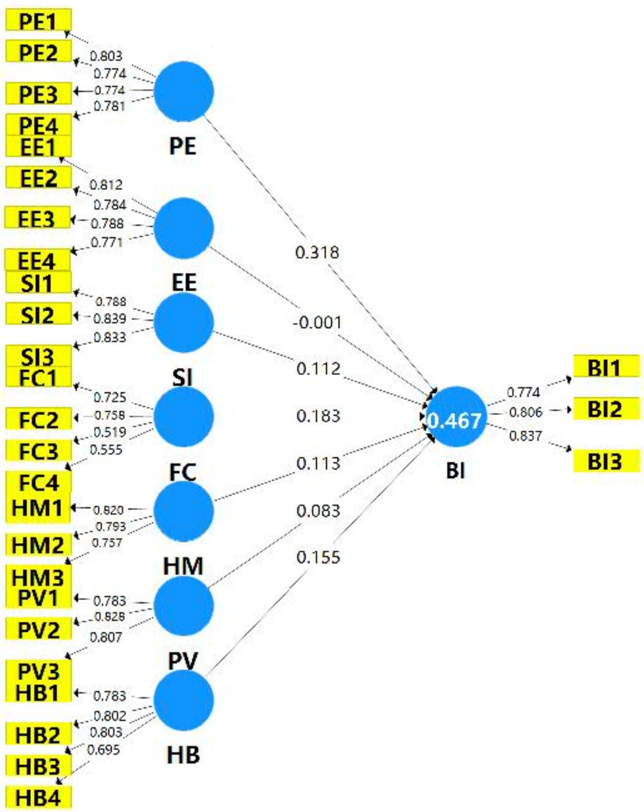

Figure 6. PLS analysis without PI

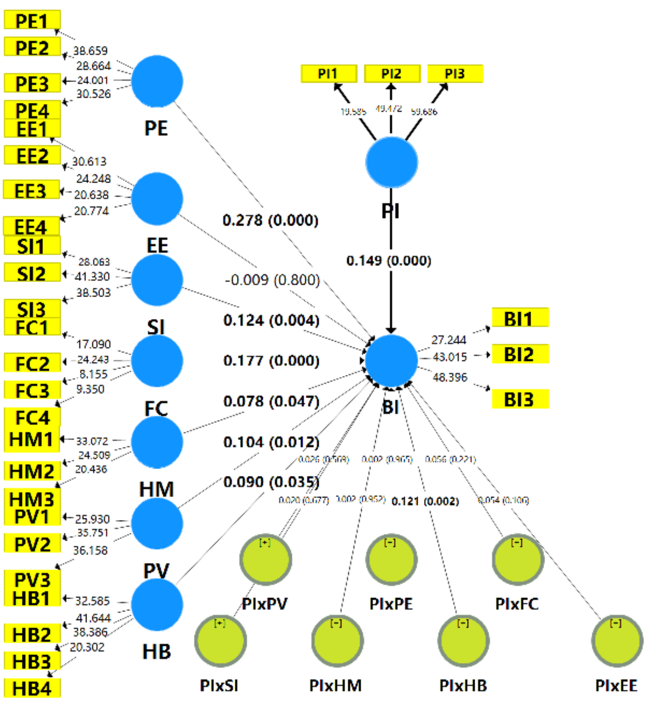

Figure 7. PLS analysis result 2 with PI

6.1 Theoretical Implication

This study tested empirical evidence and proposed seven determinants of consumers' acceptance of AI in leisure activities, including expected performance of AI, social circle, facilitating conditions, pleasure derived from using AI, price value, user habit and Personal Innovativeness. Effort Expectancy has no significant effect towards consumers' BI because of users' familiarity with AI technologies.

This study extended the UTAUT 2 model by introducing an additional factor—Personal Innovativeness. As a fundamental factor in users' adoption of AI, the Beta Value of PI (0.149) ranks the third, only after PE and FC. And the Beta Value of PI as a moderating effect on HB is 0.12. Venkatesh et al., proved the original UTAUT 1 model predicts 30% of the variance in user intentions, but in this study, the UTAUT 2 model integrating Personal Innovativeness factor increased the prediction to 51.2% of the variance in AI technology adoption. This study provides an integrated UTAUT 2 model with Personal Innovativeness and can be assessed for further theoretical evaluation.

Table 6. Results of PLS-SEM analysis in research model

Factor→ BI	Beta Value	P-Value	Outcome
H1: PE → BI	0.28	0.00	Supported
H2: EE → BI	-0.01	0.80	Not supported
H3: FC → BI	0.18	0.00	Supported
H4: SI → BI	0.12	0.00	Supported
H5: HM → BI	0.08	0.047	Supported
H6: PV → BI	0.10	0.01	Supported
H7: HB → BI	0.09	0.04	Supported
H8: PI moderates HB	0.12	0.00	Supported

6.2 Practical Implication

This study contributes to the explanation of the determinants in AI acceptance and can provide an insight for AI manufacturers or leisure industries to better understand consumer behaviors. The research illustrated that expected performance is the most significant factor to adopt AI (β=0.278), which means consumers have high expectation of AI. AI developers should improve user experience by increasing efficiency of their leisure activities so as to reach leisure goals. The Beta Value of FC (β=0.177) ranks the second, demonstrating that clear understanding and multiple means such as online access of useful resources and explanatory videos can help users to have higher use intention of AI. Other significant factor like Social Influence implies that good group interaction will generate positive word-of-mouth and encourage the use of AI. And for Hedonic Motivation, AI service should be designed in an entertaining and interactive way to attract consumers. Price Value is also a consideration when leisure activity provider introduce AI into their overall service.

7 Limitation & Future Research

There are some limitations in this study. Firstly, though several constructs were adopted into the research model to explore consumers' intention to use AI technology, there might be other potential constructs such as perceived risk, initial trust and interaction with AI that this research did not evaluate. Secondly, behavioural intention and actual use is two different concepts and this study only cover for the former part and future research should be done to assess the actual usage of AI. Thirdly, multi-group analysis (MGA) can considered to further evaluate dataset by dividing them into different groups.

With the use of AI, humans can focus more on valuable and creative work. "AI + Leisure" is not to replace the people working in service industry, but to help them minimize the burden of repetitive workload, whether physical or digital. The development of Artificial Intelligence and robotics industry will have significant implication for the allocation of domestic and overseas resources in tourism.

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2. Exploration of Cultural Industry Innovative Talent Cultivation in Regional Economy, 2018 University Teaching Cultivation Project in Shenzhen Institute of Information Technology.

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Biography

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Appendix 1. Demographic information (n=560)

		Frequency	%
Gender	Male	319	56.96
	Female	241	43.04
Occupa-tion	Government/Institute Officer	86	15.36
	Technician/Professional	205	36.61
	Staff	124	22.14
	Businessman/Servant	78	13.93
	Former/Fishman/Flock Master etc	9	1.61
	Operators/Producer/Transporter	32	5.71
	Soldier	2	0.36
	Others	24	4.29
Age	15-19	21	3.57
	20-29	283	50.54
	30-39	191	34.11
	40-49	49	8.75
	50-59	13	2.32
	Over 60	3	0.54
District	Northeast China	42	7.50
	Eastern China	128	22.86
	Northern China	110	19.64
	Southern China	133	23.75
	Central China	69	12.32
	Northwest China	16	2.86
	Southwest China	58	10.36
	HK, Macau & Taiwan	4	0.71
Monthly Income	1000-4999 RMB	122	21.79
	5000-9999 RMB	234	41.79
	10000-19999 RMB	107	19.11
	20000-29999 RMB	43	7.68
	30000-39999 RMB	17	3.04
	40000-49999 RMB	8	1.43
	50000-99999 RMB	20	3.57
	Over 100000 RMB	9	1.61
AI Service Categorie	Food & Restaurants	54	9.64
	Hotels & Residence	66	11.79
	Outgoings	118	21.07
	Traveling	166	29.64
	Shopping	61	10.89
	Leisure	83	14.82
	Others	12	2.14

Appendix 2. Mean, Standard Deviation, Excess Kurtosis and Skewness

	Mean	Std.Dev	Excess Kurtosis	Skewness
PE1	5.47	1.20	1.58	-0.94
PE2	5.65	1.19	1.55	-1.08
PE3	5.44	1.25	1.18	-0.95
PE4	5.50	1.27	0.80	-0.88
EE1	5.25	1.40	0.26	-0.79
EE2	5.30	1.36	0.15	-0.71
EE3	5.39	1.38	0.83	-0.96
EE4	4.98	1.38	0.20	-0.59
SI1	4.45	1.48	-0.41	-0.33
SI2	4.73	1.39	-0.19	-0.37
SI3	4.61	1.42	-0.17	-0.47
FC1	4.90	1.51	-0.02	-0.68
FC2	5.15	1.40	0.50	-0.86
FC3	5.38	1.37	0.69	-0.89
FC4	5.33	1.36	0.38	-0.83
HM1	5.57	1.41	0.64	-1.02
HM2	5.43	1.28	0.94	-0.92

Appendix 2. Mean, Standard Deviation, Excess Kurtosis and Skewness (continue)

	Mean	Std.Dev	Excess Kurtosis	Skewness
HM3	5.31	1.39	0.58	-0.92
PV1	4.07	1.56	-0.60	-0.15
PV2	4.51	1.48	-0.41	-0.29
PV3	4.94	1.40	0.22	-0.66
HB1	4.24	1.53	-0.53	-0.33
HB2	3.47	1.72	-0.86	0.28
HB3	3.24	1.82	-1.06	0.31
HB4	4.49	1.44	-0.25	-0.43
PI1	4.26	1.69	-0.83	-0.26
PI2	5.19	1.38	0.32	-0.78
PI3	5.09	1.38	0.44	-0.81
BI1	5.53	1.18	1.02	-0.88
BI2	5.24	1.23	0.41	-0.60
BI3	5.26	1.29	1.05	-0.96