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Decoding User Intentions Towards AI Chatbot Services Under the Impact of Social Influences

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Abstract

Artificial intelligence chatbot services (AICSs) have become more popular than ever in the current scenario despite much debate about their positives and negatives. This study aims to explore the links between social influences (SIs) related to community views, opinions, and the environment that affects individuals' transformation of their hedonic motivation (HM) and expectations (CEs), shedding light on their intention to continue using AICSs. Via a deductive approach and mixed methods, a cross-sectional study was conducted to evaluate the measurement and structural models with the participation of 332 university students in South Vietnam through an online survey (using Google Forms). Partial least squares structural equation modelling (PLS-SEM) was applied in this study. Research findings show that social influence (SIs) have positive impacts on HM, CEs (including performance and effort expectations), and behavioural intention toward AICS usage (BI). CEs and HM play intermediary roles in the relationship between SIs and BI. Notably, customer habit (HBT) has adverse moderating effects on relationships such as “SI and CEs” and “HM and BI,” clarifying customer experience about their intention to continue using AICSs in the current context. As a result, the research findings are expected to provide significant theoretical and practical implications for AI service managers and developers.

Keywords:

AI Chatbot Services;
Social Influences;
Performance Expectancy;
Effort Expectancy;
Hedonic Motivation;
Behavioral Intention.

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1- Introduction

In conjunction with changes in the human condition and perception, the role of artificial intelligence (AI) in interacting with individuals has become feasible [1]. The contributions of AI related to humans have been demonstrated in a lot of sectors such as medicine [2, 3], economics [4], sociology [5, 6], psychology [7], and education [8, 9]. Among the valuable applications of AI, AICSs are distributed by developers and have become popular with users worldwide with their features and deep learning capabilities [10]. Via the process of "deep learning" and "personalisation", AICSs not only accompany users in fundamental issues such as purchasing, suggesting trading channels [11], or simply answering questions but also solve specialised problems such as analysis, synthesis, script writing, and programming [10]. AICSs have affirmed their importance in customer interaction, such as providing 24/7 operation in the trading activities of enterprises related to consumer shopping behaviour, customer relationship management, wholesaling, and retailing [12, 13]. In such an emerging country, Vietnam, AICSs have significantly enhanced businesses' ability to respond and distribute products/services to customers during and after COVID-19 [12]. Developers who distribute AICSs often offer trial (free version) and commercial (user-charged version) mechanisms, which leads to AI Chatbot features being somewhat different in features between versions [14]. This raises questions regarding the future role of AICSs, namely whether AI Chatbots can replace people or assist humans in interactive activities using words or writing

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such as ChatGPT [12]. Given this premise, studying user intent and considering the intention to use AICSs in the current context is a practical necessity.

Research on the intention to use AICSs is a pressing topic that scholars are very interested in, considering both its positive and negative aspects [15, 16]. Notably, the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) are applied by most scholars to explain the behaviour or intention to use AICSs [17-20]. Related to UTAUT and extended UTAUT, "performance expectancy (PE), effort expectancy (EE), social influences (SIs), trust (TR), perceived risk (PR), facilitating condition (FC), and extrinsic motivation (EM)" are factors affecting the intention to use AICSs mostly recommended in recent studies [17, 18, 21, 22]. Notably, almost all studies applied UTAUT to explore the intention to use AICSs mentioned HM, SIs, and EE as independent variables [17, 18, 22] while rarely considering the relationship between them leading to behavioural intention [23]. In addition, SIs are regarded as factors strongly affecting customers' motivation [24] and their satisfaction with products or services [25], while no studies have examined the impact of SIs on customers' expectations. Thus, investigating the effects of SIs connected to AICS usage on customer motivation and expectation, which leads to continued usage intention, is a research gap that should be addressed.

Unlike UTAUT, research applied TAM and extended TAM on the intention to use AICSs focused on perceived ease of use (PEOU), perceived usefulness (PU), perceived enjoyment, service quality, and information quality [14, 26, 27]. Also based on the Tam model, some other studies have expanded independent variables such as information and communication technology self-efficacy, self-directed learning with technology [28], or academic content creation, information seeking, novelty [14], or user acceptance and trust, user experience and satisfaction, communication effectiveness [29]. However, some drawbacks are also discovered based on this research approach, such as a lack of consideration of customer experience in terms of emotion and value [29] or the motivations with which customers interact with AI Chatbots [19]. Notably, Kleine et al. [30] indicated that PEOU and PU could not provide accurate personal feedback or, in other words, user experience. Kleine et al. [30] also called for papers to take into account "both stable individual differences and temporal variations in user experience". Therefore, decoding aspects related to customer experience leading to continued intention to use AICSs is a notable research gap.

On the other hand, a number of studies approach the intention to use AICSs through the impact of cognitive factors and service characteristics. Cognitive factors influencing the intention to use AICSs are often considered as self-learning capabilities, knowledge acquisition, knowledge application [31] or perceived intelligence, perceived empathy, perceived status quo usage value, and perceived future usage value [32]. Service characteristics in previous studies are found to influence the intention to use AICSs as task characteristics, technology characteristics, and social network characteristics [33], or functional value, social value, emotional value, and epistemic value [34], or anthropomorphic features [35, 36]. In this approach, researchers argue that they are limited in customer experience, such as different versions of AICSs (free and paid) [35]. Besides, post-use psychological experiences or user habits (HBTs) are also limitations in studies on AICS usage intention [35]. Zhao & Min [32] also called for papers to decipher the motivations leading to the intention to continue using AICSs. Notably, in the study of Sundjaja et al. [37], the intention to continue using AICSs was explained through a complex mediating mechanism, including disclosure, chatbot quality, PU, confirmation, and satisfaction under the influence of technology anxiety. However, the research results still show limitations in customer experience due to weak links in the model; for example, technology anxiety has a limited impact on chatbot quality and disclosure, and PU has a weak impact on confirmation, leading to customer satisfaction [37]. These findings suggest that future studies should have a better approach and enhance customer experience through expectation fulfilment, shedding light on the intention to continue using AICSs.

In line with the above findings, the research gaps in this context are related to customer expectations (CEs) and motivations under the influence of individuals and social contexts leading to their behavioural intentions [32]. In addition, customer experiences leading to continued usage intentions towards AICSs also need to be explored [35]. This study aims to examine the links between SI, HM, EE, and AICS usage intention to address these research gaps via the Stimulus-Organism-Response (S-O-R) paradigm [38] linked with the components of UTAUT2 [39] such as SI, HM, CEs (PE and EE), and HBTs. In addition, to address customer experience, AICS usage habits are examined to moderate the relationships such as SI and HM, SI and EE, SI and AICS usage intention, HM and AICS usage intention, and EE and AICS usage intention. HBT, in this context, is understood as the process of using AICSs and is a process of formation after the experience [40]; therefore, the mediating role of HBT on the relationships in the model will bring a deep understanding of the customer's experience.

The rest of the study is broken into five sections. Section 2 covers the theoretical framework, research hypotheses, and proposed conceptual model, while Section 3 goes into the research technique, which includes data collection, scaling, and data analysis processes. Section 4 presents the research findings, while Section 5 discusses them in terms of practical and theoretical implications. Finally, Section 6 includes conclusions, shortcomings, and future directions.

2- Theoretical Framework and Hypothesis Development

2-1- Theoretical Framework

The S-O-R framework has been applied by previous studies on behavioural intention or behaviour [41]. It has proven its suitability in explaining the individual's cognitive process in response to environmental stimuli leading to an individual's response, such as intention or behaviour [42]. In the context of the intention to use AICSs, the application of S-O-R to develop variables and model the intention to use AICSs is still limited [43]. In the study of Rafiq et al. [43], consumer's intention to adopt AI chatbots was directly influenced by cognitive and affective attitudes (as organisms) and indirectly impacted by stimulus factors such as perceived usability, interactivity, perceived intelligence, and anthropomorphism. Although the application of S-O-R to explain behavioural intention to use AICSs is limited, S-O-R is an opportunity to build new variables or relationships when combined with other previous theories to fully explain the mechanism of individual intention formation [43, 44].

According to Camilleri [17], behavioural intention can be defined as "an individual's readiness to perform given behaviours". The intention to use AICSs is defined as "the individuals' willingness to repeatedly perform specified behaviours, including utilising the application of information technologies such as AI Chatbots" [17]. Similarly, behavioural intention to use AICSs is approached from many angles, including perceived value and benefits [32, 37], service characteristics [33], emotions [34] and beliefs [31, 45]. To decode the intention to use AICSs from different perspectives, the most widely applied previous behavioural models and theories, such as the Theory of planned behaviour (TPB) [31, 46], TAM [30, 47], and UTAUT [18, 48, 49]. However, behavioural theories and models have certain limitations [42], and scholars have continuously expanded and improved them over time to better explain behavioural intention or behaviour [18].

In the context of the intention to use AICSs, UTAUT2 is considered a theory with more inheritance and a more complete explanation of the attributes of intention or behaviour than previous models and theories such as TPB, TAM, and UTAUT [18, 21]. Specifically, "performance expectancy" is defined as "the degree to which individuals believe that using a system will help them improve their job performance", while "effort expectancy" refers to "the degree of ease associated with the use of a system" [17]. Notably, PE and EE are regarded as an inheritance from the expectancy-value theory [17]. In addition, "hedonic motivation (HM)" refers to "the fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance and use" [39]. HM makes UTAUT2 different by considering internal user motivations instead of EM, like UTAUT [21]. In addition, the completeness in explaining the behavioural intention of UTAUT2 cannot be without the role of HBT, and HBT is a variable not yet included in UTAUT [21]. Surprisingly, in most studies on AICS usage intention, little attention has been paid to HBT and its influence on user intention [18, 22].

As mentioned, this study approaches AICS usage intention via the S-O-R mechanism to address the current research gaps in AICS usage intention. SI refers to "a process that may lead individuals to change their opinions, beliefs, or behaviours due to social interactions with others" [21]. In the current study, SI is considered a stimulus factor that affects CEs, HM, and the intention to use AICSs. Organisms refer to CEs and HM, which directly affect customer response (the intention to use AICSs). By integrating the components of UTAUT2 into S-O-R, unique relationships are established when considering the mediating roles of CEs and HMs, allowing to address existing gaps, such as the impact of SI leading to CEs and HMs, as well as the intention to use AICSs. In addition, the research gap related to customer experience when using AICSs is also clarified in the mediating effect of HBTs on the links in the theoretical model.

2-2- Hypothesis development

The numerous studies on AICS usage intentions highlight the importance of SI, which significantly impacts individuals' intents and decisions [17, 22, 50]. According to Acosta-Enriquez et al. [50], "SI in the context of adopting AICSs" refers to " the degree to which an individual perceives that other people important to him or her believe that he or she should use AI". Chen et al. [18] and Wijaya et al. [51] observed that SI was not connected with AICS usage intention, whereas Camilleri [17] discovered that SI had a favourable influence on AICS usage intention.

H1: SI is positively linked with AICS usage intention;

In addition, SI also refers to "the effect of individuals on others or the impact of social environments on individuals" [52]. Numerous prior investigations have investigated the relationship between SI and consumer motivation [24, 53], but no study on AICS usage intention has been undertaken. Sitar-Tăut [54] indicated that SI was positively associated with HM in the context of mobile learning. According to Pop et al. [24], social media was positively associated with altruistic and egoistic motives. Similarly, Kumar & Pandey [55] reaffirmed the relationship between SI and customer motivation in their study of green purchase intention.

H2: SI is positively linked with HM when using AICSs.

Previous educational research has shown a link between SI and expectations [56], while studies on intention to use AICSs have not addressed this. In the study of Lasselle & Smith [57], opinions from students' relatives significantly influence their expectations of choosing a university. In the current context, the study hypothesises that the influence of surrounding people positively impacts AICS users' expectations.

H3: SI is positively linked with CEs when using AICSs.

The links between HM and AICS usage intention have been demonstrated in previous research [17, 58]. According to Acosta-Enriquez et al. [50], HM refers to " the pleasure or enjoyment derived from the use of a technology". Similar to Paraskevi et al. [58], Camilleri [17] indicated that HM was positively associated with behavioural intention (BI) towards AICS usage. Surprisingly, García de Blanes Sebastián et al. [59] insisted that HM was not associated with AICS usage intention. Hence, reconsidering this relationship in the current theoretical model is necessary.

H4: HM is positively associated with AICS usage intention;

Regarding the links between CEs and AICS usage intention, former scholars have confirmed when applying UTAUT [17] and UTAUT2 [51]. Although the studies were on AICS usage intention, they had different results on the relationship between CEs and AICS usage intention. Specifically, in the study of Camilleri [17], both PE and EE had positive effects on AICS usage intention, while in the study of García de Blanes Sebastián et al. [59], both PE and EE had no relationship with AICS usage intention. Notably, Wijaya et al. [51] found that PE positively impacted BI towards usage intention, while EE had no ties with BI.

H5: CEs are positively associated with AICS usage intention;

As stated, the role of HBT in recent studies on AICS usage intention has received less attention and mainly considered the direct relationship between HBT and AICS usage intention [51]. HBT refers to "the disposition in which people tend to perform behaviours automatically due to prior learning" [50]. In line with this, Fleetwood [40] defined HBT as "behavioural dispositions to repeat well-practised actions given recurring circumstances". In other words, HBT is seen as a post-experience formation process and how HBT affects other relationships in the current model, such as SI and HM, SI and CE, SI and BI, HM and BI, and CE and BI. The moderating role of HBT has been mentioned in previous research [60, 61]; however, the research results showed that HBT has a negative or positive impact on the relationship between trust and intention. Until now, no study has examined the moderating effect of HBT on relationships such as SI and HM, SI and CE, SI and BI, HM and BI, and CE and BI. However, little research has examined the mediating effects of HBT on the links between utilitarian motivation and purchase intention (PI), HM and PI [62], or PE and the intention to switch to retail apps, or EE and the intention to switch to retail apps [63]. Therefore, exploring the impact of HBT on the relationships between variables when integrating components of UTAUT2 into S-O-R allows us to address the research gap related to customer experience in studies of AICS usage intention.

H6a: HBT moderates the link between SI and HM when using AICSs;

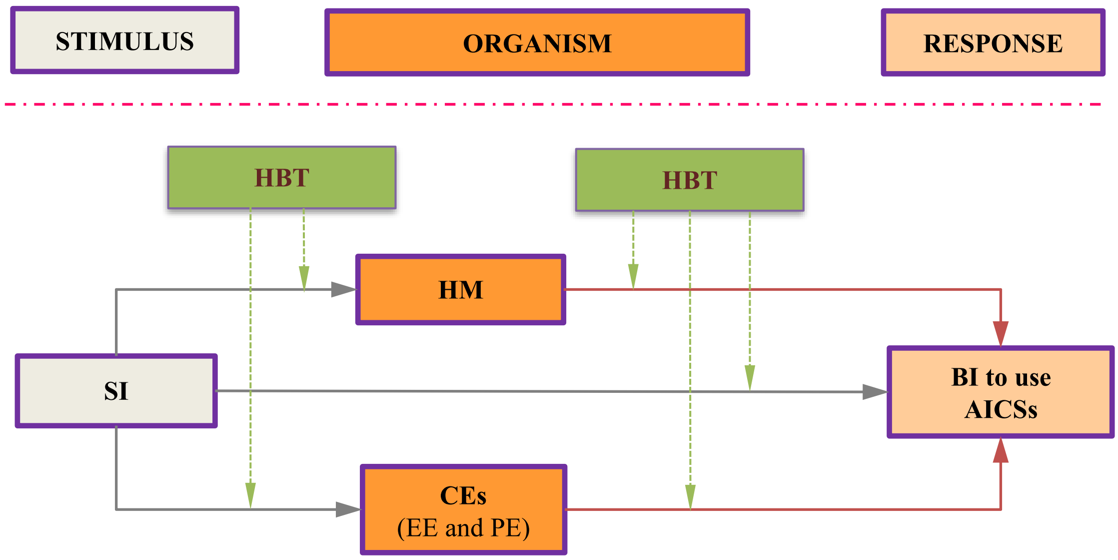
H6b: HBT moderates the link between SI and CEs when using AICSs;

H6c: HBT moderates the link between SI and AICS usage intention;

H6d: HBT moderates the link between HM and AICS usage intention;

H6e: HBT moderates the link between CEs and AICS usage intention.

The conceptual model towards intention to use AICSs is presented in Figure 1.



**Note: SI: Social influence, HM: hedonic motivation, CEs: Customer expectations, EE: Effort expectancy, PE: Performance expectancy, BI: Behavioural intention, HBT: Customer habit.*

Figure 1. The conceptual model towards intention to use AICSs

3- Research Methodology

A mixed method linked with the “deduction” approach was applied in this study [44]. In the first phase, the study identified the research objectives via the research gaps in the literature on AICS usage intention. Then, the initial measurement scales were built based on the relevant research and theories. A focus group and expert discussion related to the initial scales were conducted to investigate some issues that needed adjustment before releasing official scales (Figure 2). In the second phase, the scales’ reliability was tested in the pilot study to ensure all indicators were well-fit [44]. Then, “evaluating measurement and structural models was conducted after checking the common method biases” (VIF test) [44].

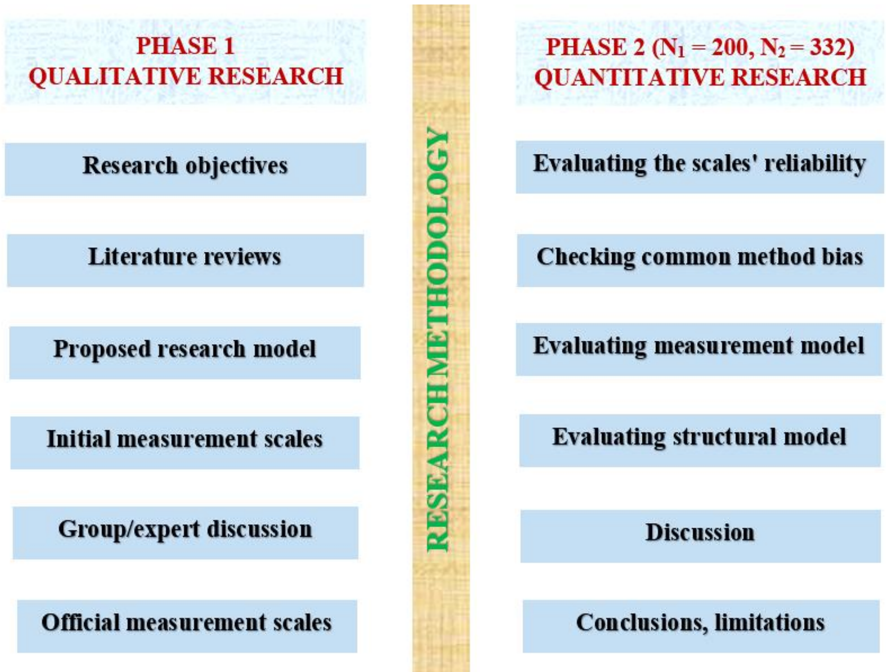


Figure 2. The methodological research design (adapted from [44])

3-1- Data Collection and Measurement Instrument

Primary data were collected through online surveys on the Google Forms application. The survey link was sent to respondents, and when they agreed to participate, they provided their email addresses to the collector. The survey subjects were university students who regularly used AICSs in the southern region of Vietnam. Although convenience sampling was used for a cross-sectional study, sample size was ensured through the 10-time rule [64]. In the main study, the total number of samples sent to respondents was 630, resulting in 332 valid samples. The details of respondents’ profiles are presented in Table 1. The official scales and the pilot test results are presented in Table 2.

Table 1. The demographic characteristics

	Description	N = 332	Rate (%)
Gender	Female	112	33.7
	Male	220	66.3
Student	Freshman	78	23.5
	Sophomore	55	16.5
	Junior	146	44.0
	Senior	53	16.0
Major	Business administration	36	10.8
	Finance banking - Accounting	38	11.4
	Journalism	28	8.4
	Marketing	61	18.4
	Restaurant-Hotel-Tourism	37	11.1
	Linguistics	36	10.8
	Law	96	28.9

Table 2. Measurement scales

Factors	Indicators	Corrected Item-Total Correlation	Cronbach's alpha (α)	Sources
Social Influence (SI)			**0.904**	Venkatesh et al. [39] and Camilleri [17]
SI1	I often hear friends talking about using AICSs or AI technology in learning;	0.845	0.832	
SI2	My teachers often recommend using AICSs in learning;	0.816	0.857	
SI3	General trends in AI Chatbot usage in the community influenced my decision to use it;	0.767	0.898	
Hedonic Motivation (HM)			**0.930**	Venkatesh et al. [39] and Camilleri [17]
HM1	I enjoy interacting with AI Chatbots;	0.850	0.904	
HM2	I love the personalisation that AI Chatbots offers;	0.857	0.900	
HM3	I like the answers that the AI Chatbots give;	0.865	0.893	
Customer Expectations (CEs)				Venkatesh et al. [39] and Camilleri [17]
Effort Expectancy (EE)			**0.902**	
EE1	I quickly learned how to use AI Chatbots;	0.727	0.891	
EE2	I know how to direct the AI Chatbots to answer precisely the questions and tasks I need;	0.887	0.840	
EE3	I find it easy to use AI Chatbots to learn various skills;	0.737	0.889	
EE4	Using AI Chatbots is similar to other apps I am using;	0.790	0.871	
Performance Expectancy (PE)			**0.851**	Venkatesh et al. [39] and Camilleri [17]
PE1	I have fully understood the benefits that AI Chatbots can bring;	0.652	0.827	
PE2	I know AI Chatbots can help my learning;	0.204	0.874	
PE3	I feel like I need more guidance to understand the benefits of using AI Chatbots;	0.662	0.827	
PE4	Using AI Chatbots helped me gain insight into topics that interest me;	0.678	0.824	
PE5	I believe that AI Chatbots can improve my performance in solving school assignments and projects;	0.716	0.820	
PE6	I can save a lot of time looking up necessary information when using AI Chatbots;	0.828	0.811	
PE7	I use AI Chatbots as my tutor;	0.273	0.864	
PE8	The overall value that AI Chatbots bring to my learning process is worth considering;	0.568	0.836	
PE9	AI Chatbots help me identify and develop the professional skills needed for my career;	0.656	0.827	
Customer Habit (HBT)			**0.807**	Venkatesh et al. [39] and Camilleri [17]
HBT1	Without a mandatory element, I still see the need to use AI Chatbots;	0.676	0.727	
HBT2	Looking up information with AI Chatbots is almost a habit of mine;	0.675	0.718	
HBT3	I use AI Chatbots when needed;	0.639	0.770	
Behavioural Intention Towards AICS Usage (BI)			**0.872**	Venkatesh et al. [39] and Camilleri [17]
BI1	I am fully open to and will use AI Chatbots for learning purposes if they are helpful for my field of study;	0.765	0.835	
BI2	Most of my tasks will be done through AI Chatbots;	0.753	0.837	
BI3	I will use AI Chatbots to look up information in daily life;	0.817	0.825	
BI4	I will use AI chatbots for study and work in the future;	0.619	0.882	
BI5	I want to explore more about the features and applications of AI Chatbots in learning.	0.615	0.854	

To ensure the initial scale's reliability (N1= 200), the "Cronbach's Alpha index" should be higher than 0.708 [64], and the "corrected item-total correlation (CI-TC)" should be higher than 0.3 [65]. Thus, PE2 and PE7 were eliminated since the CI-TC values were smaller than 0.3. Therefore, all indicators (25 items) were retained and used for the primary survey (N2 = 322).

3-2-Analysis Procedures

Before evaluating the measurement and structural models with the official survey results (322 valid samples), the study checked for common biases (multicollinearity). The results showed that the inner model VIF was less than 3.3 and ensured that the model did not violate multicollinearity following the instructions of Hair Jr et al. [64].

To assess the measurement model, “convergent validity (outer loading ≥ 0.7; AVE ≥ 0.5), composite reliability (CR ≥ 0.6 or α ≥ 0.708), and discriminant validity (Fornell-Larcker or Heterotrait –Monotrait ratio)” were checked following the instructions of Hair Jr et al. [64]. Then, to assess the structural model, “Partial Least Squares Structural Equation Modelling (PLS-SEM)” was applied [44].

4- Results

4-1-Measurement Model

According to the results in Table 3, the CR and discriminant validity (DV) were ensured since all CR and α indexes are higher than the threshold (CR ≥ 0.6 or α ≥ 0.708). Specifically, the minimum CR and α indexes are 0.862 and 0.760, respectively.

In addition, DV was satisfied since “every latent variable's square root of AVE is higher than the correlation between it and every other latent variable” [66]. The details of the Fornell-Larcker criterion values are shown in Table 3.

To ensure the convergent validity (CV), Hair Jr et al. [64] indicated that the outer loading value should be higher than 0.708. According to the research results (Table 3), PE1 and PE3 were eliminated since the outer loadings of PE1 and PE3 were lower than 0.7 [64]. Therefore, in the following analysis step, the remaining indicators will continue to be used to evaluate the structural model.

Table 3. Results of the measurement model evaluation

Factors	Items	Loading	α	CR	AVE	Fornell-Larcker criterion results					
Behavioural intention	BI1	0.731									
	BI2	0.721									
	BI3	0.828	**0.808**	**0.866**	**0.565**	**0.752**					
	BI4	0.737									
	BI5	0.736									
Effort expectancy	EE1	0.809									
	EE2	0.875	**0.848**	**0.898**	**0.688**	0.528	**0.829**				
	EE3	0.830									
	EE4	0.801									
Customer habit	HBT1	0.854									
	HBT2	0.846	**0.760**	**0.862**	**0.676**	0.623	0.399	**0.822**			
	HBT3	0.763									
Hedonic motivation	HM1	0.920									
	HM2	0.910	**0.901**	**0.938**	**0.834**	0.695	0.458	0.433	**0.913**		
	HM3	0.910									
Performance expectancy	PE1	**0.689**									
	PE3	**0.674**									
	PE4	0.774									
	PE5	0.812	**0.873**	**0.902**	**0.570**	0.750	0.399	0.491	0.606	**0.794**	
	PE6	0.854									
	PE8	0.743									
	PE9	0.720									
Social influence	SI1	0.849									
	SI2	0.854	**0.831**	**0.899**	**0.747**	0.576	0.456	0.477	0.522	0.479	**0.864**
	SI3	0.889									

4-2-Structural Model

The direct path coefficients of the structural model are presented in Table 4 and Figure 3. Notably, all direct path relationships expected to have positive relationships are supported at 5% and 1% significance levels. H1 was supported with a significance of 5% and the positive impact of SI on BI was confirmed (β= 0.085, p < 0.05). The remaining hypotheses (H2, H3, H4, and H5) were supported with a significance of 1%. In addition, the study's confidence interval [2.5%, 97.5%] does not contain the value 0, which indicates that the values are statistically significant (Table 4). Therefore, the positive correlations of SI on HM (β= 0.395, p < 0.01), SI on CEs (β=0.356, p < 0.01), HM on BI (β= 0.251, p < 0.01), and CEs on BI (β=0.453, p < 0.01), were confirmed.

Table 4. Results of the structural model evaluation

Hypotheses	Associations	P.C	S.D	T.S	P	Bias	2.5%	97.5%	Results
H1	SI → BI	0.085	0.041	2.087	0.037	-0.002	0.004	0.164	SP
H2	SI → HM	0.395	0.053	7.404	0.000	0.001	0.292	0.502	SP
H3	SI → CEs	0.356	0.049	7.201	0.000	0.001	0.254	0.448	SP
H4	HM → BI	0.251	0.042	5.995	0.000	0.002	0.165	0.329	SP
H5	CEs → BI	0.453	0.053	8.607	0.000	-0.002	0.352	0.559	SP

Note: P.C = Path coefficient, S.D = Standard deviation; T.S = T statistics; SP = supported, $R^2_{BI} = 0.727$, $R^2_{CEs} = 0.423$, $R^2_{HM} = 0.319$.

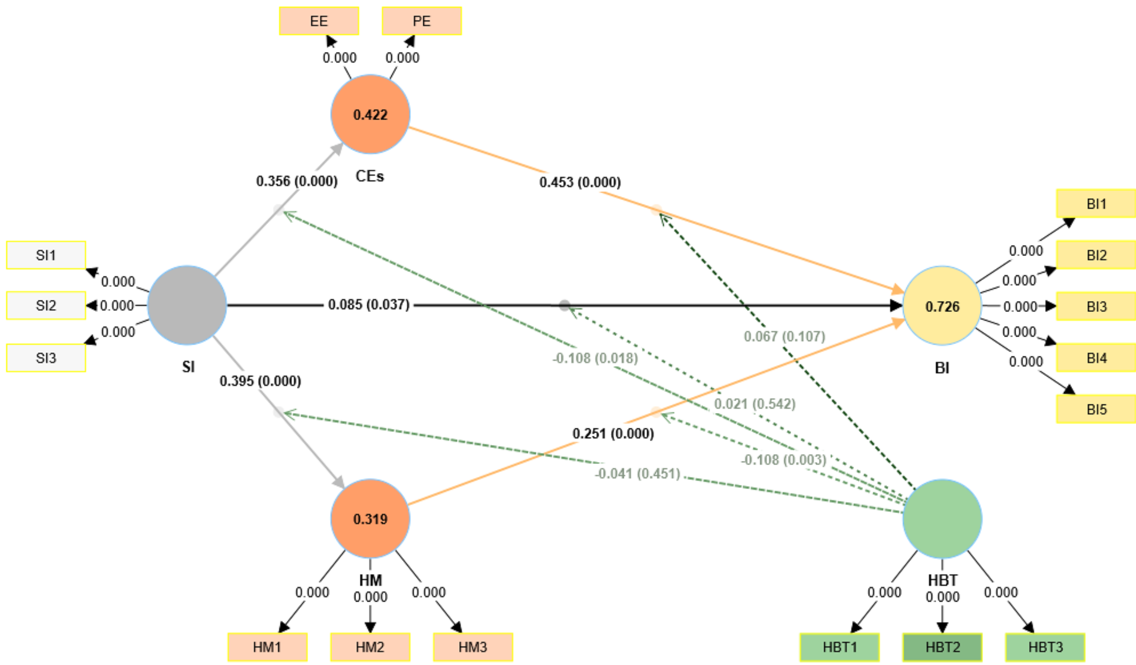


Figure 3. Results of the path coefficients

Table 5, Figures 4 and 5 present the mediating and moderating impacts of the conceptual model. All the path coefficients of the mediating relationships in the theoretical model are supported at the 1% significance level ($\beta_{SI \rightarrow CEs \rightarrow BI} = 0.161$, $p < 0.01$; $\beta_{SI \rightarrow HM \rightarrow BI} = 0.099$, $p < 0.01$). Similarly, the study's confidence interval [2.5%, 97.5%] does not contain the value 0, indicating that the values are statistically significant (Table 5). Hence, the mediating roles of CEs and HM were confirmed.

Besides the mediating effects in the theoretical model, the moderating effects are remarkable. The results showed that HBT negatively moderated the links between SI and CEs ($\beta_{HBT \times SI \rightarrow CEs} = -0.108$, $p < 0.05$) and between HM and BI ($\beta_{HBT \times HM \rightarrow BI} = -0.108$, $p < 0.01$). In other words, HBT weakens the relationships between SI and CEs and between HM and BI (Figures 4 and 5). In this case, the confidence interval [2.5%, 97.5%] does not contain the value 0, which indicates that the values are statistically significant (Table 5). Therefore, H6b and H6d were supported at the 5% significance level. In addition, H6a, H6c, and H6e were not supported since the confidence interval [2.5%, 97.5%] contains the value 0 (or $p > 0.05$) (Table 5).

Table 5. Results of mediating and moderating impacts

	Associations	P.C	S.D	T.S	P	Bias	2.5%	97.5%	Results
Mediating effects									
	SI → CEs → BI	0.161	0.032	5.059	0.000	0.000	0.106	0.233	SP
	SI → HM → BI	0.099	0.022	4.442	0.000	0.001	0.060	0.146	SP
Moderating effects									
H6a	HBT × SI → HM	-0.041	0.055	0.754	0.451	-0.007	-0.149	0.060	RJ
H6b	HBT × SI → CEs	-0.108	0.045	2.376	0.018	0.004	-0.185	-0.009	SP
H6c	HBT × SI → BI	0.021	0.035	0.611	0.542	0.003	-0.049	0.088	RJ
H6d	HBT × HM→ BI	-0.108	0.037	2.956	0.003	-0.006	-0.186	-0.044	SP
H6e	HBT × CEs → BI	0.067	0.042	1.613	0.107	0.005	-0.014	0.148	RJ
	HBT → BI	0.231	0.038	6.144	0.000	0.000	0.157	0.305	SP

Note: P.C = Path coefficient, S.D = Standard deviation; T.S = T statistics, SP = Supported, RJ = Rejected;

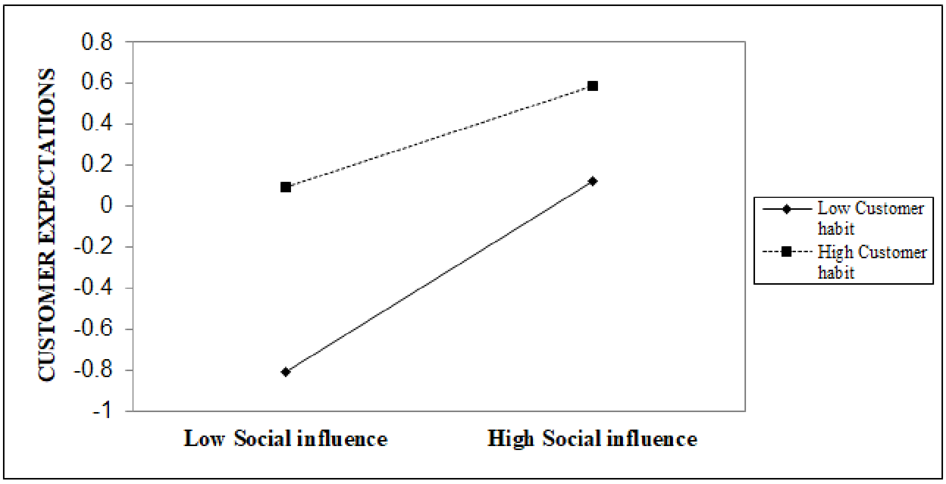


Figure 4. The moderating effect of HBT on the link between SI and CEs

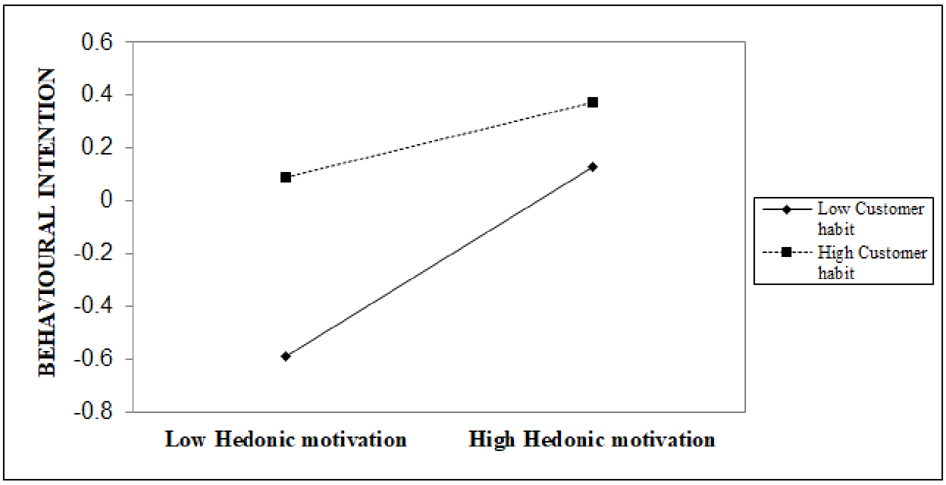


Figure 5. The moderating effect of HBT on the link between HM and BI

5- Discussion

The study has successfully modelled the intention to use AICSs by integrating components of UTAUT2 into the S-O-R framework to address the current research gaps. The elements in the theoretical model, such as SI, HM, CEs and HBT, are shown to have a high level of explanation for the intention to use AICSs ($R^2 = 72.7\%$). All initial hypotheses related to the direct effects were supported based on the research results (Table 4), shedding light on the foundation for deeper discussion. To gain a clearer view and delve deeper into the findings, this section discusses direct, mediating and moderating effects that appear in the theoretical model of the intention to use AICSs.

Regarding the positive impacts of SI on BI, HM, and CEs (H1, H2, and H3), SI has the most substantial effect on HM ($\beta = 0.395$, $p < 0.01$), followed by CEs ($\beta = 0.356$, $p < 0.01$), and has a relatively modest impact on BI ($\beta = 0.085$, $p < 0.05$). Research results reaffirm the positive impact of SI on the intention to use AICSs and are entirely consistent with previous studies such as Camilleri [17] and Biloš & Budimir [67]. These findings also show that other personal opinions, views and social environments in the context of using AICSs significantly influence customer motivation and expectations. These findings also add novelty to current research related to exploring the correlation between SI and intrapersonal transformation processes, such as their expectations and motivations. Surprisingly, HM and CEs are less frequently considered in previous studies related to SI, while they are often considered in relation to the intention to use AICSs. This result allows managers to easily shape input information and build appropriate viewpoints and policies to better meet customer expectations and enhance their motivation.

Related to the positive impacts of HM and CEs (EE and PE) on the intention to use AICSs (H4 and H5), CEs have a positive impact on BI and are higher than the impact of HM on BI ($\beta_{CEs \rightarrow BI} = 0.453$, $\beta_{HM \rightarrow BI} = 0.251$, $p < 0.01$). Although exploring the relationship between HM and BI or CEs and BI is not new, these are two essential key elements in the current model that address the current research gaps. In line with this, the unique point in these relationships is the construction of a second-order structure for the two factors EE and PE to streamline the variables that have been proven to be suitable in previous studies applying UTAUT2 [17, 67]. Similar to CE, the regenerated HM confirmed a positive relationship with the intention to use AICS and was consistent with the findings of Camilleri [17] and Biloš & Budimir [67].

The mediating roles of CEs and HM in this study are novel findings. The study results show that SI has a significant impact on the intention to use AICSs via CEs ($\beta_{SI \rightarrow CEs \rightarrow BI} = 0.161$, $p < 0.01$). In other words, PE and EE both act as mediators for the impact of SI on the intention to use AICSs. Although the impact of SI on BI via HM ($\beta_{SI \rightarrow HM \rightarrow BI} = 0.099$, $p < 0.01$) is smaller than that via CEs, this result demonstrates that HM plays a vital role in forming the intention to use AICSs. Compared with previous studies on intention to use AICS, CE, including PE and EE, are often considered independent variables and have direct relationships with BI rather than a mediating role [18, 68]. In addition, other studies have mentioned the mediating role of PE when examining the relationship between EE and BI [17, 69]; however, these studies have not considered general customer expectations as a mediating variable, including both PE and EE. On the other hand, the mediating role of HM in this study reaffirms the results of Sitar-Tăut [54], shedding light on the intention to use AICSs.

The moderating impacts of HBT on other relationships in the theoretical model are considered a highlight in the current study. Although HBT only moderates two relationships, "SI and CEs" ($\beta_{HBT \times SI \rightarrow CEs} = -0.108$, $p < 0.05$) and "HM and BI" ($\beta_{HBT \times HM \rightarrow BI} = -0.108$, $p < 0.01$), these findings significantly address the current research gaps related to customer experience and continuance intention of using AICSs. According to the research results, HBT weakens the link between SI and CEs ($\beta = -0.108$). As customers become accustomed to using AICSs, the relationship between SI and CEs decreases. In other words, the influence of people around and the environment on customer expectations decreases as the use of AICSs becomes a habit. Similarly, HBT also weakens the link between HM and BI ($\beta_{HBT \times HM \rightarrow BI} = -0.108$, $p < 0.01$). This result indicates that the HM leading to the intention to use AICSs decreases as the use of AICSs becomes a habit and differs from the study of Sharifi Fard et al. [62] in concluding that HBT does not have a moderating effect on the relationship between HM and BI. Notably, Iranmanesh et al. [63] explored the role of HBT as a moderating variable in the relationships between PE and the intention to switch to retail apps, as well as between EE and the intention to switch to retail apps. However, their findings suggest that HBT does not serve as a moderating factor in these relationships. The results of the present study examining the moderating effect of HBT on the relationship between CEs and BI are consistent with the results of Iranmanesh et al. [63].

Theoretically, the study contributes to existing models and theories on the intention to use AICSs by selectively integrating elements of UTAUT2 into the S-O-R paradigm to address current research gaps. Although the elements in the model are not new, the combination of UTAUT2 and the S-O-R paradigm allows the exploration of relationships that previous studies have not paid much attention to. Compared to prior research, the results of this study show similarities in the direct relationships of factors such as SI [70], HM [17], and CEs [70] to BI, while Wijaya et al. [51] showed opposite results when demonstrating that SI and HM have no relationship with BI. These differences in the results of previous studies are deciphered in the current study when examining the mediating roles of HM and CEs for the relationship between SI and BI [17, 22, 51, 70]. Literature shows that there are many different approaches to the intention to use AICSs in the digital age; however, the relevance of behavioural models and theories (such as UTAUT2) is still demonstrated in current studies. The results of the current study show that the intentional application of previous behavioural theories to a research topic will still be effective and theoretically relevant; however, studies need to consider the role of variables (especially mediators and moderators) that allow the theoretical model to well explain the research object. The moderating role of HBT really makes the current research highlight, paving the way to fill the research gaps related to customer experience when using AICSs [30, 37]. Furthermore, including variables that have been proved to be appropriate in earlier studies into other structures (such as second-order variable structures) would result in greater representativeness and generalisation of the observed variables' properties.

Practically, the study proved the importance of SI on variables in the research model, such as HM, CEs, and intention to use AICSs. This result provides managers and policymakers with a clear picture of the relationships between stimuli (people's opinions, both direct and indirect, and the surrounding environment) and the internal transformation of individuals regarding HM and expectations, shedding light on their intention to use AICSs. Notably, HM and CEs are significant elements in the establishment of intention to use AICSs in the current context, and increasing their influence can boost AICS's user intention. Another point to note is the customers' usage habits towards AICSs. Obviously, the research results show that HBT weakens relationships such as SI→CEs, and HM →BI while other relationships are not influenced by HBT. However, when HBT is below the mean, the slopes of SI and CEs, or HM and BI, are much higher than when HBT is high; thus, this is a finding that managers need to pay attention to so as not to attenuate relationships such as between SI and CEs and between HM and BI.

6- Conclusion

The study fully models the process of intention formation for using AICSs, identifies the triggers (SI) that lead to individual transformations (CEs and HM), and sheds light on current research gaps in customer experience. The research results confirm that the intention to use AICS is not a tendency at all but a clear perception of the attributes of HM and CEs, indicating the direct and indirect effects of SI on BI. In addition, the study found that customer experience through the effects of HBT on the relationships between SI and CE and between HM and BI. This result suggests that customer experience, when too familiar with AICS, will weaken the relationship between SI and CE and HM and BI. Besides, this study reaffirms the suitability of the UTAUT2 model in the current context when applied to explain the intention to continue using AICSs through significant direct relationships such as SI→ BI, HM → BI, CEs → BI, despite the differences in theoretical model construction. As a result, the study's findings contribute both theoretically and practically to current theories on the intention to utilise AICSs.

Besides the contributions of this research, some drawbacks have been discovered. First, the study limited the sample to university students; therefore, future studies should consider a broader context, such as individuals in businesses or organisations who regularly use AICSs. Second, although the study exploited the variables in the UTAUT2 model combined with the S-O-R paradigm, it is clear that the current model lacks the emotional element. Previous studies have shown that the role of emotions is significant in the context of factors such as the views and opinions of leaders, colleagues, and people around them. Therefore, future studies need to exploit the emotional aspect to more fully consider the process of forming the intention to use AICSs. Finally, the study is cross-sectional, and convenience sampling is used. Therefore, the study will have certain limitations when considering homogeneous sample data. Future studies can develop a specific and longitudinal survey group, creating opportunities for more apparent findings on the transformation within the individual.

7- Declarations

7-1- Author Contributions

Conceptualization, D.T.T. and T.D.T.; methodology, D.T.T. and T.D.T.; software, D.T.T. and T.N.P.; validation, A.N.K., T.D.T., and N.T.C.P.; formal analysis, D.T.T. and T.D.T.; investigation, D.T.T. and N.T.C.P.; resources, D.T.T. and T.D.T.; data curation, T.N.P., A.N.K., and N.T.C.P.; writing—original draft preparation, D.T.T. and T.D.T.; writing—review and editing, D.T.T. and T.D.T.; visualization, T.N.P., A.N.K., and N.T.C.P.; supervision, D.T.T. and T.D.T.; project administration, D.T.T.; funding acquisition, D.T.T. and T.D.T. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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