Preliminary Study to Understand the Gen Z Student's Behaviour towards Adoption AI Chatbots with the Moderating Role of Gender Using Modified UTAUT2

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ABSTRACT

The prompt progression of Artificial Intelligence (AI) spread to all sectors including the education sectors. The development of AI chatbots as advanced instruments can enhance the teaching and learning in higher learning institutions. Regardless of powerful chatbots, the effective implementation use of AI chatbots among students in higher learning institutions depends on a composite relationship among technological, behavioural, and demographic circumstances. Furthermore, this study focuses on the Generation Z (Gen Z) students that are known as digital citizens born between the middle 1990s and early 2010s. The main objective of this preliminary study is to understand the Gen Z students' behaviour towards adoption of AI chatbots by using Unified Theory of Acceptance and Use of Technology (UTAUT2). There are two variables added to this study. The population for this study is the students from public and private higher learning institutions in Terengganu. Hence, this study is using the convenience sampling technique to get the respondents. However, the sample size for this study is 118 students based on the G-Power. The instruments for this study were conducted online and as a result, 205 respondents have completed and returned the questionnaires. The data collected is analysed using SPSS 28.00 and PLS 4.1. There are nine behavioural intentions factors and 12 hypotheses that were constructed for this study. Nevertheless, only four were supported and the rest eight were rejected. As a result, the gender as a moderating effect between behavioural intention and adoption use of AI chatbots was rejected. This study is suggested to apply in other higher learning institutions to see the comparison between them. Furthermore, it is recommended for future research to use new variables as mediating effects or new variables as moderating effects.

Keywords: Adoption AI chatbots, UTAUT2, Students' behaviour, Gen Z

INTRODUCTION

Nowadays, AI chatbots are tremendously implemented in higher learning institutions to enhance the process of teaching and learning. However, the behavioural factors that influence the adoption of AI chatbots among Gen Z students in higher learning institutions remain lack of investigations [31][32]. Gen Z can be categorised as extraordinary digital literacy, favouring prompt interaction, and they anticipated in technology motivated clarification [1]. A modified UTAUT2 model can replicate the adoption of AI chatbots usage in higher learning institutions by adding two factors such as trust and technology anxiety and demonstrated to have influence on adoption of AI technology in the past studies [2][3]. Nevertheless, past studies implemented the UTAUT2 model to explore the adoption of technology, gender as a moderating variable that influences the behavioural factors towards adoption of technology is rarely being considered in the study. Previous study has revealed that the awareness of technology adoption diverges between male and female students especially on behavioural factors such as social influence [4]. Therefore, this preliminary study is conducted to understand the Gen Z student's behaviour towards the adoption of AI chatbots by using the modified UTAUT2 model as well as to analyse the moderating role of gender in this study.

LITERATURE REVIEW

Generation Z and Technology Adaption

The first generation born utterly in the digital era is the generation Z that was born between 1997 and 2012 [6]. Gen Z are considered by their extraordinary technological knowledge, multitasking capability, and favour in flexible-first interaction. Conversely, past research indicates that Gen Z demonstrates quicker concentration time and superior probabilities for user experience and validity

UTAUT2 Model

This study is using the modification of original UTAUT2 [7] and extends this model by adding two more constructs related to adoption of AI chatbots among students in higher learning institutions. Based on the recommendation from the past studies, it is suggested to understand the alternative behavioural components of adoption of AI chatbots that is crucial for development of chatbot for improving chatbot execution in higher learning institutions. Therefore, the constructs used in this study are performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HT).

PE can be defined as the level of believing using AI chatbots will improve the student performance in completing their task and learning process in higher learning institutions. Past studies discovered PE has a positive impact towards the intention to adopt AI in the learning process [8][9]. Besides, PE was found as the most influential construct of a student's intention to adopt AI [9]. EE construct is known as the perceived ease of using AI chatbots, where the user adopts chatbots more readily when they believe the system is straightforward and involves minimal effort [10][11]. SI construct is the degree to which individuals comprehend that significant others think that they must use AI chatbots, affecting intention and usage [10][12][15]. FC displays user's awareness of available resources, technical support, and infrastructure that allow efficient chatbot use [10][13].

HM portrays the pleasure, excitement, or enjoyable experience consequent from relating with AI chatbots, which can improve adoption intentions [10][11]. Past study indicates that HM plays a strong role in behavioural intentions to adapt technology [15]. PV measures the interchange between perceived benefits and costs when the user feels that AI chatbots' benefits compensate for financial or effort-related costs, the adoption of AI chatbots multiplies [10][14]. Habit indicates the level to which chatbots use becomes usual or routine, drastically forecasting ongoing usage [10][13].

H1: The higher the behavioural intention, the higher the student's adoption of AI chatbots in higher learning institutions.

H2: Performance expectancy positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

H3: Effort expectancy positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

H4: Social influence positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

FC displays user's awareness of available resources, technical support, and infrastructure that allow efficient chatbot use [10][13].

H5: Facilitating conditions positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

H6: Hedonic motivation positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

H7: Price value positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

H8: Habit positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

H9: Habit positively influences the behaviour intention to adopt AI Chatbots moderated by gender in higher learning institutions.

Modified UTAUT2 Model for This Study

Therefore, the **modified UTAUT2** in this study preserves PE, EE, SI, FC, HM, PV and HT, while theoretically adding two more constructs that includes *Trust* and *Technology Anxiety* to better explain student adoption behaviour in AI motivated circumstances.

Trust displays user's idea that AI chatbots are trustworthy, secure, able for delivering precise assistance, making it an essential element of adoption [16][17]. Otherwise, researchers have recommended adding new constructs such as trust to capture emotional and ethical components [18]. Distinguished risk can be moderated by trusting the new technologies and readily participating with new technologies such as financial services or smart homes [34][35]. 32 studies found that the integrating trust in UTAUT2 develops expectation of user acceptance of new technology and trust can be a mediator between UTAUT2 behavioural factors and behavioural intention [34]. TA is the worry or nervousness users feel when relating with AI directed tools, that lead to decreasing adoption of AI chatbots [19][20]. Past studies showed that TA can be identified as moderating variable or external variables that can reduce the behavioural intention of using new technologies. [36][37]. Technology anxiety was commonly used to highlight the gaps in non-adoption studies especially in education and healthcare sectors [36][37][38]. As a result, past studies recognized that the academicians with high technology anxiety were less likely to adopt the new technologies [36].

H10: Performance expectancy positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

H11: Performance expectancy positively influences the behaviour intention to adopt AI Chatbots in higher learning institutions.

Gender as a Moderating Variable

Information systems literature has extensively examined the gender differences in technology adoption. Past studies indicated that men reveal deeper insights of performance expectancy, while community and emotional factors are able to influence women. [21][22]. For this study, gender may moderate how users assess the behavioural intentions used in this study. Male users are more reactive to PE and EE [12]. In contrast, female users are persuaded by SI and HM [12].

H12: The behavioural intention is positively related to adoption of AI chatbots moderated by gender in higher learning institutions.

UTAUT2 in AI Chatbots Adoption in Higher Learning Institution

PE, EE, and HM are found to be substantial forecasters of AI Chatbots adoption in higher learning institutions [11]. Besides, SI and Habit intensely influence intention to use AI chatbots among students [23]. On the other hand, numerous studies found out that addition of trust in UTAUT2 for AI chatbots in higher learning institutions has revealed enhanced clarifying power [24]. Furthermore, gender moderated the relationship between UTAUT2 constructs and behavioural intentions to use AI chatbots in higher learning institutions [25]. Therefore, the conceptual framework for this study is illustrated in Figure 1.

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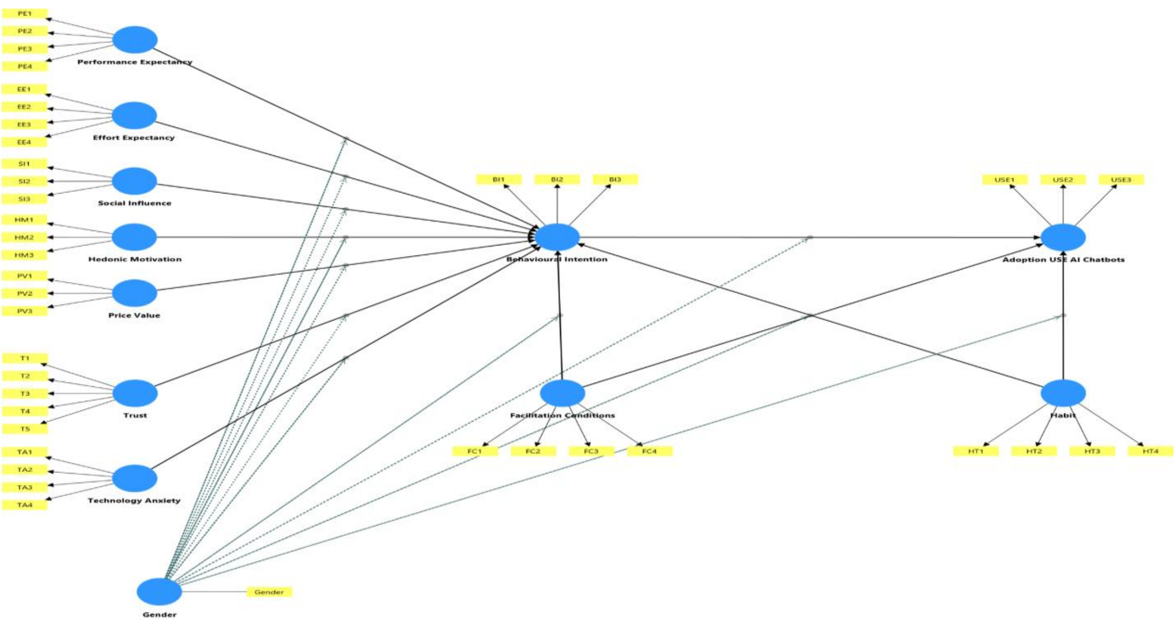
Figure 1: Conceptual Framework



RESEARCH METHODOLOGY

The study has been conducted to full time students from public and private higher learning institutions in Terengganu. Therefore, this study is limited only to the students in Terengganu and to test their adoption of AI Chatbots during their study. Hence, this study is using the convenience sampling technique to get the respondents. According to G-Power, the sample size for this study based on the construct is 118 respondents [26]. The instruments for this study were conducted online and this study was able to get 205 completed and returned questionnaires more than the required sample size. The survey instruments were adapted by modified UTAUT2 that included nine behavioural intention factors towards adoption use of AI chatbots [21]. The survey instruments are using both five-point Likert scale and seven-point Likert scale. The data collected from the respondents were analysed using SPSS 28.00 and PLS 4.1.

RESULTS AND FINDINGS

Profile of Respondents

Table 1.0: Demographic Background

Variable	**Frequency**	**Percent (%)**
Gender		
Male	46	22.40
Female	159	77.60
Total	**205**	**100.0**
Age (Generation Z)		
18 – 20	118	57.60
21 – 23	82	40.00
24 - 26	5	2.40

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Total	**205**	**100.00**
Higher Learning Institution		
Public	194	94.6
Private	11	5.40
Total	**205**	**100.0**
AI Chatbots		
ChatGPT only	75	36.60
ChatGPT, Gemini	38	18.50
ChatGPT, MS Copilot	22	10.70
ChatGPT, Gemini, Perplexity	20	9.80
ChatGPT, Gemini, MS Copilot	18	8.80
ChatGPT, Gemini, Perplexity, MS Copilot	10	4.90
ChatGPT, Perplexity	9	4.40
ChatGPT, Perplexity, MS Copilot	6	2.90
Others	7	3.50
Total	**205**	**100.00**

According to Table 1, 159 respondents (77.6%) were female, and 46 respondents were male (22.4%). The majority of the respondents' age between 18 – 20 with 118 students (57.6%) followed by 82 students' age between 21 – 23 (40%) and only five students' age between 24 – 26 (2.4%). As a result, 198 students were using ChatGPT as one of tools of AI chatbots in this study and only 75 students (36.6%) only use ChatGPT as a tool of AI chatbot.

Table 2: Crosstabulation

Behaviour Intention and Gender

I regularly use AI Chatbots in my study. * Gender Crosstabulation Count				
		Gender		**Total**
		Female	**Male**	
I I regularly use AI Chatbots in my study.	**Very strongly disagree**	**2**	**0**	**2**
	Strongly disagree	**9**	**1**	**10**
	Disagree	**19**	**2**	**21**
	Not sure	**36**	**11**	**47**

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XI November 2025

	Agree	**50**	**19**	**69**
	Strongly agree	**31**	**5**	**36**
	Very strongly agree	**12**	**8**	**20**
Total		**159**	**46**	**205**

Table 2.1: Crosstabulation 1

50 female students agree that they use AI chatbots regularly in their study followed by 31 female students who strongly agree and only 12 female students with very strongly agree to use AI chatbots regularly in their study. Besides, 19 male students agree to use AI chatbots regularly followed by 5 male students who strongly agree and 8 students with very strongly agree to use AI chatbots regularly in their study.

AI Chatbots usage is a pleasant experience. * Gender Crosstabulation Count				
		Gender		**Total**
		Female	**Male**	
AI Chatbots usage is a pleasant experience.	**Very strongly disagree**	**1**	**1**	**2**
	Strongly disagree	**4**	**0**	**4**
	Disagree	**11**	**2**	**13**
	Not sure	**48**	**15**	**63**
	Agree	**42**	**13**	**55**
	Strongly agree	**38**	**7**	**45**
	Very strongly agree	**15**	**8**	**23**
Total		**159**	**46**	**205**

Table 2.2: Crosstabulation 2

Majority of the students including male and female students acknowledge that AI chatbots are a pleasant experience. 95 female students agree that AI chatbots are a pleasant experience and only 28 male students, of which more than half male students agree the same thing.

I currently use AI Chatbot as a supporting tool in my study. * Gender Crosstabulation Count				
		Gender		**Total**
		Female	**Male**	
I currently use AI Chatbots as a supporting tool in my study.	**Very strongly disagree**	**0**	**1**	**1**
	Strongly disagree	**5**	**1**	**6**
	Disagree	**11**	**0**	**11**

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XI November 2025

	Not sure	**32**	**12**	**44**
	Agree	**49**	**6**	**55**
	Strongly agree	**45**	**12**	**57**
	Very strongly agree	**17**	**14**	**31**
Total		**159**	**46**	**205**

Table 2.3: Crosstabulation 3

14 male students very strongly agree to use AI chatbots as a supporting tool in their study followed by 12 male students who strongly agree and 6 male students with agree that AI chatbots as a supporting tool in study. In contrast, the large number of female students agree that AI chatbots as a supporting tool in study. 49 female students agree, followed by 45 female students strongly agree and 17 female students very strongly agree that AI chatbots as a supporting tool in study.

Construct	**Item**	**Loading**	**CR**	**AVE**
Effort Expectancy	EE1	0.897	0.935	0.783
	EE2	0.866		
	EE3	0.912		
	EE4	0.865		
Facilitating Conditions	FC1	0.898	0.921	0.745
	FC2	0.898		
	FC3	0.889		
	FC4	0.759		
Hedonic Motivation	HM1	0.957	0.968	0.909
	HM2	0.956		
	HM3	0.947		
Habit	HT1	0.895	0.946	0.813
	HT2	0.931		
	HT3	0.893		
	HT4	0.887		
Performance Expectancy	PE1	0.851	0.927	0.762
	PE2	0.895		
	PE3	0.883		

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	PE4	0.861		
Price Value	PV1	0.818	0.911	0.775
	PV2	0.927		
	PV3	0.891		
Social Influence	SI1	0.925	0.951	0.867
	SI2	0.931		
	SI3	0.936		
Trust	T1	0.875	0.932	0.732
	T2	0.844		
	T3	0.831		
	T4	0.893		
	T5	0.833		
Technology Anxiety	TA1	0.753	0.898	0.691
	TA2	0.685		
	TA3	0.932		
	TA4	0.927		
Use AI Chatbots	USE1	0.881	0.908	0.768
	USE2	0.879		
	USE3	0.868		
Behaviour Intention	BI1	0.837	0.924	0.802
	BI2	0.914		
	BI3	0.933		

Table 3: Convergent Validity

Table 3 presents the dataset, named Student Adoption to AI Chatbots (n=205), used to assess the reflective measurement model in Figure 1. The exogeneous variables data where performance expectancy consists of four indicators, effort expectancy consists of four indicators, facilitating conditions with four indicators, habit with four indicators, hedonic motivation with three indicators, price value with three indicators, social influence with three indicators, trust with five indicators, and technology anxiety consist of four indicators. In contrast, the endogenous variables data were behavioural intention with three indicators and use AI chatbots with three indicators.

In addition, Table 3 presents the reliability and validity of the study. The composite reliability (CR) values >0.70 indicated that these constructs have adequate level of internal consistency. Thus, the average variance extracted

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(EVA) values has met the satisfactory level of AVE with >0.50. The results showed that items in each construct explain more than 50% of the construct variance [27]. Item loading higher than 0.5 for indicator reliability is a necessity [28]. However, there are no item loadings that had value <0.50 and deleted in this study.

	BI	EE	FC	HT	HM	PE	PV	SI	TA	T
EE	0.545									
FC	0.592	0.854								
HT	0.652	0.464	0.540							
HM	0.532	0.732	0.748	0.449						
PE	0.709	0.821	0.845	0.550	0.777					
PV	0.458	0.532	0.655	0.461	0.538	0.596				
SI	0.649	0.486	0.609	0.704	0.433	0.603	0.555			
TA	0.186	0.079	0.092	0.366	0.083	0.167	0.267	0.435		
T	0.689	0.624	0.704	0.704	0.598	0.707	0.605	0.678	0.319	
USE	0.779	0.678	0.740	0.581	0.653	0.772	0.459	0.544	0.107	0.677

Table 4: Discriminant Validity (HTMT)

Table 4 shows the discriminant validity of all entry variables have been established by using the heterotrait-monotrait (HTMT) ratio of correlation criterion [29]. The discriminant validity was determined in the measurement model when the correlative values correspond to the respective constructs that do not exceed the HTM 0.90 criterions threshold. All HTMT data in this study do not exceed the 0.90 criterion threshold.

	BETA	SE	T VALUES	P VALUES	VIF	F2	DECISION
BI -> Adoption USE AI Chatbots	0.533	0.102	5.227	0.000	6.583	0.104	SUPPORTED
Gender x BI -> Adoption USE AI Chatbots	-0.160	0.138	1.164	0.122	6.674	0.007	NOT SUPPORTED
FC -> Adoption USE AI Chatbots	0.364	0.068	5.368	0.000	1.571	0.204	SUPPORTED
FC -> BI	0.146	0.197	0.743	0.229	18.343	0.003	NOT SUPPORTED
HT -> Adoption USE AI Chatbots	-0.101	0.106	0.948	0.172	6.085	0.004	NOT SUPPORTED
HT -> BI	0.105	0.236	0.444	0.329	20.016	0.001	NOT SUPPORTED
Gender x HT -> Adoption USE AI Chatbots	0.257	0.149	1.726	0.042	6.697	0.019	SUPPORTED

EE -> BI	-0.189	0.174	1.088	0.139	17.271	0.005	NOT SUPPORTED
HM -> BI	-0.195	0.214	0.913	0.181	17.918	0.005	NOT SUPPORTED
PE -> BI	0.605	0.191	3.170	0.001	14.587	0.059	SUPPORTED
PV -> BI	0.146	0.163	0.900	0.184	9.215	0.005	NOT SUPPORTED
SI -> BI	0.185	0.146	1.273	0.102	9.548	0.008	NOT SUPPORTED
TA -> BI	-0.184	0.146	1.262	0.104	8.530	0.009	NOT SUPPORTED
Trust -> BI	0.112	0.229	0.489	0.313	18.303	0.002	NOT SUPPORTED

Table 5: Path Coefficient and Hypotheses Testing and Effect Size

The bootstrapping procedure has been applied to test the hypotheses for this study and generate results for each path relationship in Table 5. Bootstrap sub-samples with 1,000-sample cases have been computed to allow the procedure to estimate the model of each sub-sample [33]. There were 12 hypotheses tested and only four hypotheses were supported. The path relationship between the behavioural intention and adoption to use AI chatbots was positively related, ß=0.00, p<0.001 at the 95% confidence level. Facilitating conditions positively related to adoption use of AI chatbots with ß=0.00, p<0.001 at the 95% confidence level. Thus, performance expectancy is positively related to behavioural intention, ß=0.00, p<0.001 at the 95% confidence level. Gender on the other hand mediated the relationship between habit and adoption use of AI chatbots with ß=0.42, p<0.001 at the 95% confidence level. Lastly, the performance expectancy was positively related to behavioural intention, ß=0.01, p<0.001 at the 95% confidence level. Gender was not moderated the relationship between behavioural intention and adoption use of AI chatbots, ß=0.122, p<0.001 at the 95% confidence level.

Table 5 presents the effect size (f2) of all the exogenous constructs on the endogenous construct. The *f*2 effect size values have exhibited the importance of each exogenous construct to the endogenous construct. The value of 0.02 has a small effect size, 0.15 has a medium effect size, and 0.35 has a medium-to-large effect size [4]. The effect size of behavioural intention on adoption to use AI chatbots is (*f*2=0.104) is medium effect size.

CONCLUSION

Since the scope of this study is limited to only higher learning institutions from public and private in Terengganu only, this study only generalises the result for this state only. To conclude, performance expectancy was proven as the most influential behavioural intentions factor on adoption to use AI chatbots in this study [8][9]. Gender moderating effects in this study fail to support the hypotheses and only habit has a positive effect on adoption to use AI chatbots moderated by gender. Even though many behavioural intentions factors were rejected in this study, the behavioural intention to adopt use of AI chatbots are positively related and supported the hypothesis. Since this is only the preliminary study, it is recommended to apply the same instruments with other higher learning institutions and to add new constructs as mediated variables or to use other moderated variables.

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