

THE ROLE OF ANONYMITY IN ARTIFICIAL INTELLIGENCE BASED CHATBOT USAGE BY UNIVERSITY STUDENT AT MEDAN

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(Received: 28 April 2025, Revised: 29 May 2025, Accepted: 12 June 2025)

Abstract

AI Chatbot is a computer program integrated with artificial intelligence designed to interact with humans and provide useful information. AI Chatbot offers anonymity, one of the factors motivating someone to use it since they feel safe. Indonesian students nowadays inhibit shyness to ask questions and participate in learning due to anxiety factors and fear of negative judgment. Therefore, it is necessary to conduct a test to understand the extent of acceptance factors of AI Chatbots. This research aims to examine the effect of anonymity variable on the use of AI Chatbots among university students at Medan using the UTAUT2 model. A survey was conducted on 421 students. Using the Structural Equation Modeling (SEM) model with the help of SmartPLS software, this study introduces the anonymity variable in the UTAUT2 model, which has a positive and significant effect on students' behavioral intention to use AI Chatbots. These findings also show that price value and habit have a positive and significant effect on behavioral intention, also habit and behavioral intention effect students' behavior towards AI Chatbots at Medan. However, performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation do not affect the students' behavioral intention and behavior towards AI Chatbots.

Keywords: *Anonymity, Artificial Intelligence, Chatbot, UTAUT2*

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1. INTRODUCTION

The development of Artificial Intelligence (AI) technology at present is inevitable. This has simultaneously resulted in increased interaction between humans and computers, culminating in the emergence of Chatbot development [1]. Chatbot (Chatting Robot) is a computer program developed to interact with humans and provide desired information and data thanks to its ability to process data through Natural Language Processing (NLP) technology and mimic human-like conversations and interactions [2]. Chatbots have successfully introduced a new aspect in the world of technology that can be used to assist human work in various fields [3]. Research from David Fonseca and Francisco José García-Peñalvo states that the technological ecosystem present in today's world can be integrated into education with efforts to increase students' academic interest in

learning and access to learning materials, not limited to interactions between teachers and students [4]. This has also been proven by several previous studies that discuss the role of AI Chatbots in education [5], where AI Chatbots are capable technological tools that can be integrated into education [6]. There is research on the use of AI Chatbots by students showing student satisfaction in using AI Chatbots that are able to provide actual, quality, and quick responses to the questions they ask [7]. This can certainly be one solution in dealing with the trend of students in Indonesia who are now shy to ask questions and participate in learning due to factors of anxiety, fear of negative judgment, lack of understanding of the material, and lack of development of questioning skills [8]. Based on research conducted by Emmelyn Croes and Marjolijn Antheunis, there are interesting research results where the reason someone uses Chatbots is for self-

disclosure, which is the disclosure of information about themselves to others, in this case to Chatbots, due to the anonymous nature of AI Chatbots. AI Chatbots now also mimic human behavior that can provide responses like everyday human conversations (human-like behavior) so that Chatbot users feel more comfortable asking questions and consulting with more complete information disclosure to chatbot entities whose identities are unknown [9].

According to Marx [10], Anonymity theoretically means a state without a name or known identity. This refers to the identity of Chatbots that offer anonymity where their identity is unknown to the person who intends to use them. One of the biggest problems faced by humans is their internal feeling of embarrassment about asking questions or presenting more complete information to fellow humans, which can be demonstrated through research on the use of AI Chatbots in the psychological field of mental health [11]. These users express that one of their reasons for using chatbots is due to their comfort in communicating with chatbots that have anonymous characteristics, allowing them to be more courageous in expressing their opinions and asking more specific questions. This is also in line with previous research on young people's perceptions of using Social Chatbot technology, where they consider chatbots to offer anonymity so they are not afraid that what they discuss could be judged by the technology, or by fellow humans, because conversations with chatbots are private [12]. The anonymity of a technology can enhance a person's perception and their intention to use that technology [11-12].

The UTAUT (Unified Theory of Acceptance and Use of Technology) model is a psychological model or framework that can be used to analyze factors influencing individual behavior towards the acceptance of technology use, introduced by Venkatesh in 2003 [14]. However, there were several limitations of the UTAUT model, so in 2012, the UTAUT2 model was developed to address these limitations and expand understanding of the factors that influence technology acceptance and use. This model formulates 4 main frameworks, namely Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, as well as 3 new constructs that complement the previous framework: Hedonic Motivation, Price Value, and Habit. Then 3 moderating variables are outlined to moderate this framework: Age, Gender, and Experience [14-15]. The UTAUT2 model was chosen as the research method because it can provide a more comprehensive approach and has been empirically tested to understand the factors that influence interest in accepting current technology use, especially in this context of Artificial Intelligence (AI) based Chatbot technology that can help organizations and application developers to plan more effective technology implementation for the future in supporting education. The age moderating variable

will not be tested in this research as the research aims to study technology use among university students who have an age range of 18-24 years .

Based on the explanations and issues mentioned above, the hypotheses proposed in this research are Performance Expectancy positively influences Behavioral Intention toward AI Chatbot among university students in Medan city (H2), Effort Expectancy positively influences Behavioral Intention toward AI Chatbot among university students in Medan city (H2), Social Influence positively influences Behavioral Intention toward AI Chatbot among university students in Medan city (H3), Facilitating Conditions positively influence Behavioral Intention toward AI Chatbot among university students in Medan city (H4a), Facilitating Conditions positively influence Use Behavior of AI Chatbot among university students in Medan city (H4b), Hedonic Motivation positively influences Behavioral Intention toward AI Chatbot among university students in Medan city (H5), Price Value positively influences Behavioral Intention toward AI Chatbot among university students in Medan city (H6), Habit positively influences Behavioral Intention toward AI Chatbot among university students in Medan city (H7a), Habit positively influences Use Behavior of AI Chatbot among university students in Medan city (H7b), Anonymity positively influences Behavioral Intention toward AI Chatbot among university students in Medan city (H8), Behavioral Intention positively influences Use Behavior of AI Chatbot among university students in Medan city (H9), Gender moderates the relationship between Facilitating Conditions and Behavioral Intention toward AI Chatbot among university students in Medan city (H10a), Gender moderates the relationship between Hedonic Motivation and Behavioral Intention toward AI Chatbot among university students in Medan city (H10b), Gender moderates the relationship between Price Value and Behavioral Intention toward AI Chatbot among university students in Medan city (H10c), Gender moderates the relationship between Habit and Behavioral Intention toward AI Chatbot among university students in Medan city (H10d), Gender moderates the relationship between Habit and Use Behavior of AI Chatbot among university students in Medan city (H10e). Experience moderates the relationship between Facilitating Conditions and Behavioral Intention toward AI Chatbot among university students in Medan city (H11a), Experience moderates the relationship between Hedonic Motivation and Behavioral Intention toward AI Chatbot among university students in Medan city (H11b), Experience moderates the relationship between Habit and Behavioral Intention toward AI Chatbot among university students in Medan city (H11c), Experience moderates the relationship between Habit and Use Behavior of AI Chatbot among university students in Medan city (H11d) and

Experience moderates the relationship between Behavioral Intention and Use Behavior of AI Chatbot among university students in Medan city (H11e) [16-18]. The contribution of this research lies in the integration of the Anonymity variable into the UTAUT2 model to better understand AI chatbot adoption among university students in Medan. While prior research has examined UTAUT2 in various technology contexts, few have explored the role of anonymity as a psychological factor in educational chatbot usage. This study thus expands the UTAUT2 framework by proposing and validating a novel construct that reflects students' behavioral intention to adopt AI chatbots in higher education. The remainder of this paper is organized where Section 2 presents the research methodology, including data collection and measurement instruments. Section 3 discusses the results and analysis and Section 4 conclude the paper and offers suggestions for future research.

2. RESEARCH METHOD

2.1 UTAUT2

The UTAUT (Unified Theory of Acceptance and Use of Technology) model can be described as a psychological framework developed to analyze the factors that influence an individual's intention to use a technology. This model was first introduced by Venkatesh in 2003. UTAUT integrates elements from several existing previous technology acceptance theories, including the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). These theories form the foundation for UTAUT to serve as a more comprehensive framework for understanding user behavior in technology adoption.

In this model, Venkatesh introduced four key constructs in the development of UTAUT: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, which serve as the main factors influencing technology acceptance. Furthermore, Venkatesh also introduced four moderating variables to better understand the relationship between the predictors and an individual's behavioral intention. These variables are Age, Gender, Experience, and Voluntariness of Use, aiming to create a more tailored and effective analysis of user behavior.

In 2012, UTAUT2 was developed by Venkatesh to address the limitations of the original UTAUT and to expand the understanding of factors affecting technology acceptance and usage. This model retained the original four constructs—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—and added three new constructs: Hedonic Motivation, Price Value, and

Habit. It also retained three moderating variables: Age, Gender, and Experience. With the inclusion of these new constructs, UTAUT2 enables researchers to gain a more comprehensive understanding of the factors influencing technology usage.

2.2 Data Collection

The data collection method used in this research is a quantitative method that focuses on survey data, statistics, measurements, and previous data. The quantitative method is highly beneficial in providing a systematic and measurable approach to conducting research or analysis [20].

A questionnaire will be distributed to respondents to obtain primary data for this study. Furthermore, weighting values will be applied using the Likert scale in the questionnaire, which consists of five answer choices, as shown in the following table [21].

Table 1. Answer Choices

No.	Answer	Score
1	Very Agree	5
2	Agree	4
3	Neutral	3
4	Disagree	2
5	Very Disagree	1

2.3 Population and Sample

The population refers to a group of people, individuals, objects, or other entities that possess specific qualities and characteristics that are the focus of the research. This population is then studied by researchers to draw conclusions based on the data they provide. Meanwhile, the sample represents a portion of the population that reflects its characteristics and qualities. This approach allows for more efficient research, as researchers can analyze a subset of a large population [22]. The population used in this study consists of university students in Medan who use AI Chatbots. However, since no valid data on AI Chatbot users in Medan could be found, the Lemeshow formula will be applied to estimate the population and the number of users, which is unknown [23].

The Lemeshow formula for cases where the population size and the number of users are unknown is as follows:

$$n = \frac{Z^2 \frac{1-a/z \times P(1-P)}{d^2}}{1} \quad (1)$$

n = Total sample

Z = Z Score in credibility 95% = 1,96

P = estimated maximum = 0,5

d = alpha (0,5) or sampling error = 5%

Using the Lemeshow formula mentioned earlier, the required sample size for this study can be determined through the following calculation:

$$n = \frac{(1,96)^2 * 0,5 (1-0,5)}{(0,05)^2}$$

$$\begin{aligned}
&= \frac{3,8416 \times 0,25}{0,0025} \\
&= \frac{0,9604}{0,0025} \\
&= 384,16 \\
&= 385 \text{ respondent}
\end{aligned}$$

Thus, the required sample size is 385 respondents, representing all active university students in Medan who use AI Chatbots.

2.4 Data Analysis

The collected research data will then be used for analysis to test the hypotheses outlined above. The SEM-PLS (Structural Equation Models – Partial Least Square) method was chosen as the analytical method using the SmartPLS 3 software [24]. This method is also suitable for research involving social constructs with more complex variables [25]. This aligns with the research being conducted, as it features a broad model and aims to explore multiple relationships between variables [26]. The variables to be tested include Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, and Anonymity, with moderation effects from Gender and Experience.

2.5 Comparative Study

In 2019, a study by Tom Nadarzynski et al. explored the acceptance of AI-based chatbots in healthcare services. The independent variables included awareness, experience, perceived accuracy, premature technology, non-human interaction, cybersecurity, anonymity, convenience, and sign-posting, while the dependent variables were understanding of chatbots, AI hesitancy, and motivation for health chatbots. The findings revealed that anonymity was one of the key factors driving the use of chatbots, particularly in mental and sexual health contexts [27].

Also in 2021, Giacomo Migliore et al. studied mobile payment adoption in China and Italy by integrating the UTAUT2 model and Innovation Resistance Theory. Independent variables included ten factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and four barriers: value, risk, tradition, and image. The dependent variable was behavioral intention, with cultural dimensions like individualism and power distance as moderators. The study found that factors like performance expectancy, effort expectancy, and tradition barrier influenced mobile payment adoption, with differences between countries [28].

In 2022, Rahim Noor Irlana Mohd et al. investigated AI-based chatbot adoption in higher education institutions using a hybrid PLS-SEM and Neural Network approach. The independent variables included performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic

motivation, price value, interactivity, design, and ethics. Results showed that performance expectancy, habit, design, and ethics had a positive influence on chatbot adoption intention, while variables such as effort expectancy, social influence, and hedonic motivation were not significant [12].

In 2023, Artur Strzelecki studied the acceptance of ChatGPT by university students in higher education using an extended UTAUT model. The independent variables included performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and personal innovativeness. The findings showed that most variables had a positive effect on behavioral intention and use behavior, except for facilitating conditions, which had no influence on behavioral intention [29].

Also in 2023, Angelia et al. examined the effect of attitude on mobile banking acceptance using an extended UTAUT model. The independent variables included performance expectancy, effort expectancy, social influence, facilitating conditions, task technology fit, trust, and attitude. Moderating variables included age, gender, experience, and voluntariness of use. The results showed that social influence and attitude significantly influenced behavioral intention, while performance expectancy and trust did not. The moderating variables had no strengthening effect on the relationships [17].

Compared to previous studies, the present research focuses specifically on the adoption of AI-based chatbot applications among university students in Medan, Indonesia. While Nadarzynski et al. (2019) investigated chatbot acceptance in healthcare settings with a strong emphasis on anonymity and mental/sexual health contexts, this study shifts the domain to higher education. Similarly, although Mohd et al. (2022) and Strzelecki (2023) examined chatbot adoption in academic environments, their studies were conducted in broader or international contexts and did not explicitly include anonymity as a key factor. Furthermore, earlier research such as that by Migliore et al. (2021) and Angelia et al. (2023) focused on mobile banking and payment systems, integrating models like UTAUT2 and Innovation Resistance Theory with variables such as trust and tradition barriers, which differ significantly from the educational and chatbot context of this research. Additionally, most prior studies incorporated various moderating variables like age, gender, voluntariness of use, and cultural dimensions; however, few specifically examined the moderating effects of gender and experience in relation to AI chatbot use among students. Therefore, the research gap lies in the lack of studies that investigate AI chatbot adoption in higher education by incorporating both UTAUT2 constructs and the element of **anonymity**, particularly within the localized context of students in Medan, using **gender and experience** as moderating variables. This study aims to address that gap by

offering a more focused analysis of behavioral intention and actual use behavior related to AI chatbot applications in an academic setting.

3. RESULT AND DISCUSSION

3.1 Result

Tables Based on 388 valid responses from respondents obtained through distribution and collection, the following is a general overview of the respondents based on their university of origin, gender, and experience.

Table 2. Respondent Characteristic

Dimensions	Categories	Amount
University	Institut Bisnis IT&B	183
	UNPRI	53
	USU	41
	UPH	32
	Universitas Mikroskil	31
	Politeknik Cendana	13
	UCM	8
	PMCI	7
	UNIMED	6
	ISTP	5
	STMB MULTISMART	4
	STBA PIA	4
	WBI	3
	UMI	3
	Universitas Satya Terra	3
	Bhinneka	
	UISU	3
	MTU	2
	Menda	2
	IBBI	2
	Dharmawangsa	2
	Eka Prasetya	2
	UMA	1
	UINSU	1
Gender	Male	198
	Female	190
Experience	Less than 2 years	267
	More than 2 years	121

1. Outer Model Evaluation

The evaluation of the measurement model aims to assess the extent to which indicators represent latent variables. The testing within the measurement model includes convergent validity, discriminant validity, and composite reliability using the SmartPLS application. Below is a diagram showing the results of the measurement model evaluation using SmartPLS.

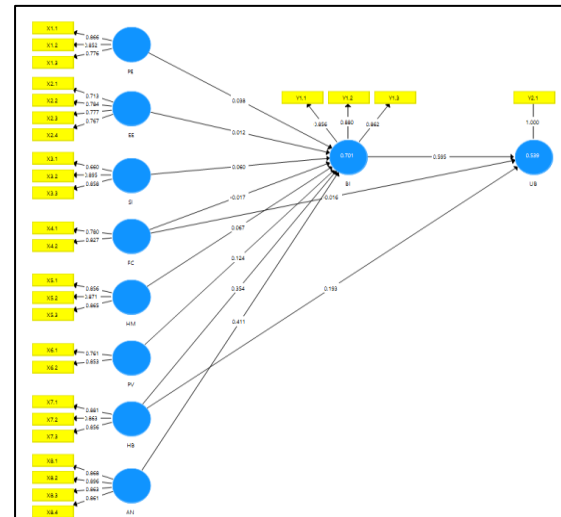


Figure. 1. Outer Model Evaluation Diagram

Convergent validity can be evaluated through the loading factor available in the SmartPLS application. For an indicator to be considered valid, the loading factor between the variable and its indicator must be greater than 0.7 (loading factor ≥ 0.7), and the AVE (Average Variance Extracted) value must exceed 0.5 (AVE ≥ 0.5). Table 3 below presents the test results for convergent validity.

Table 3. Convergent Validity Test

Variable	Description
Performance	Valid
	Valid
Expectancy	Valid
	Valid
Effort Expectancy	Valid
	Valid
Social Influence	Valid
	Valid
Facilitating Conditions	Valid
	Valid
Hedonic Motivation	Valid
	Valid
Price Value	Valid
	Valid
Habit	Valid
	Valid
Anonymity	Valid
	Valid
Behavioral Intentions	Valid
	Valid
Use Behavior	Valid

Based on Table 3, out of the 28 indicators tested, 27 indicators meet the requirements for convergent validity, while one indicator, X3.1, does not meet the

requirements because it has a loading factor value below 0.7. Therefore, the X3.1 indicator will be removed during the evaluation of the structural model (inner model).

The following are the Composite Reliability results for each variable, assessed through Cronbach's Alpha and Composite Reliability values, as shown in Table 4 below.

Table 4. Composite Reliability Test

Variable	Cronbach's Alpha	Composite Reliability	Description
X1	0.779	0.871	Reliable
X2	0.758	0.846	Reliable
X3	0.732	0.850	Reliable
X4	0.454	0.785	Reliable
X5	0.831	0.899	Reliable
X6	0.474	0.790	Reliable
X7	0.835	0.901	Reliable
X8	0.895	0.927	Reliable
Y1	0.834	0.900	Reliable
Y2	1.000	1.000	Reliable

Based on Table 4 above, it can be observed that almost all composite reliability and Cronbach's Alpha values for each variable in this study are greater than 0.7. However, some variables, such as X4 and X6, have Cronbach's Alpha values below 0.7 but composite reliability values above 0.7, indicating that these variables are still considered reliable. This demonstrates that all variables meet the required reliability criteria. Therefore, it can be concluded that all variables in this study are reliable.

2. Inner Model Evaluation

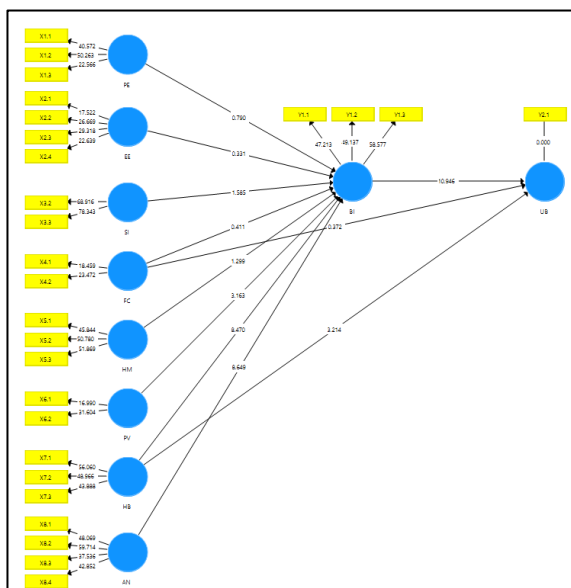


Figure 2. Inner Model Evaluation Diagram

In the inner model analysis, three stages are conducted: testing the coefficient of determination (R-Square), testing predictive relevance (Q-Square),

and hypothesis testing. The diagram below presents the results of the inner model evaluation.

An R-Square (R^2) value of 0.67 indicates that the model used is a good model. If the R-Square (R^2) value is between 0.33 and 0.67, the model is classified as moderate, while an R-Square (R^2) value below 0.33 is considered weak. The R-Square results from this study can be seen in Table 5 below.

Table 5. R-Square Calculations

Variable	R Square	R Square Adjusted	Description
Behavioral Intentions	0.701	0.695	Good
Use Behavior	0.539	0.535	Moderate

Based on Table 5 above, the values obtained for the Behavioral Intentions and Use Behavior variables indicate that this model has good observational results. The R-Square value for Behavioral Intentions shows that the independent variables in this research model explain 69.5% (0.695) of the dependent variable, while the remaining 30.5% is explained by other independent variables outside this research model. Meanwhile, the R-Square value for Use Behavior indicates that the independent variables in this research model explain 53.5% (0.535) of the dependent variable, with the remaining 46.5% explained by other independent variables outside this research model.

Predictive relevance testing is used to measure how well the observed values are predicted by the model. A Q-Square value greater than 0 indicates that the model has predictive relevance. Conversely, if the Q-Square value is less than or equal to 0, the model is considered to lack predictive relevance. The results of the Q-Square test can be seen in Table 6 below.

Table 6. Q-Square Calculations

Variable	Q-Square	Information
Behavioral Intentions	0.515	Predictive Relevance
Use Behavior	0.528	Predictive Relevance

Based on Table 6 above, the values obtained for the Behavioral Intentions and Use Behavior variables indicate that this model has good observational results. Similar to R-Square, which explains the relationship between independent and dependent variables, Q-Square describes the extent of variability in the variables within this study. The Q-Square value for Behavioral Intentions shows that 51.5% (0.515) of the variability in this variable can be explained by the model, while the remaining 48.5% is explained by other variables outside this research model. Meanwhile, the Q-Square value for Use Behavior indicates that 52.8% (0.528) of its variability is explained by the model, with the remaining 47.2% influenced by external variables beyond this research model. Since the Q-Square values are greater than zero, it can be concluded that the model used in this

study has been well-constructed and possesses predictive relevance.

Hypothesis testing is conducted using the bootstrapping method in SmartPLS 3, with a significance level of 0.05 or 5%. To evaluate whether the independent variable has a positive or negative effect on the dependent variable, the original sample value is observed. If this value is positive, then the effect is positive, and if it is negative, then the effect is negative. To determine the statistical significance of the relationship between variables, the T-Statistics value is used. A relationship is considered significant if T-Statistics > 1.96 and P-Value < 0.05. Thus, the hypothesis is accepted if T-Statistics > 1.96 and P-Value < 0.05. Conversely, the hypothesis is rejected if T-Statistics < 1.96 and P-Value > 0.05. The results of the T-Statistics and P-Value for latent variables and moderating variables can be seen in Table 7 below.

Table 7. Hypothesis Test

Hypothesis	Standard Deviation (STDEV)	P Values	Description
X1 -> Y1	0,046	0,441	Not Accepted
X2 -> Y1	0,053	0,749	Not Accepted
X3 -> Y1	0,036	0,095	Not Accepted
X4 -> Y1	0,035	0,629	Not Accepted
X4 -> Y2	0,045	0,718	Not Accepted
X5 -> Y1	0,051	0,173	Not Accepted
X6 -> Y1	0,041	0,002	Accepted
X7 -> Y1	0,042	0,000	Accepted
X7 -> Y2	0,058	0,001	Accepted
X8 -> Y1	0,046	0,000	Accepted
Y1 -> Y2	0,052	0,000	Accepted

The information presented in Table 7 above indicates that hypotheses H6, H7a, H7b, H8, and H9 meet the criteria and can be accepted.

3. Hypothesis Test for Gender as Moderator

In this study, the gender variable is divided into two groups: male and female. The respondents previously tested will be separated into two groups, consisting of 198 male respondents and 190 female respondents, who will be tested using different models.

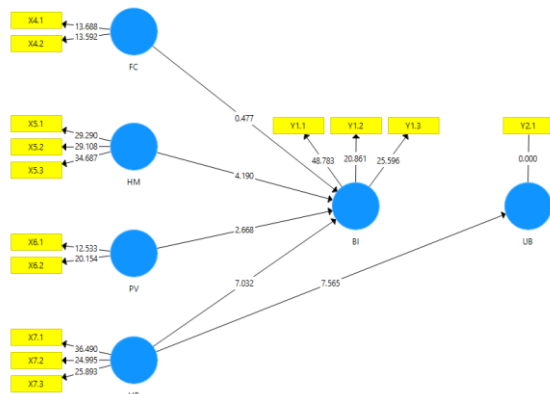


Figure 3. Outer Model Evaluation (Male)

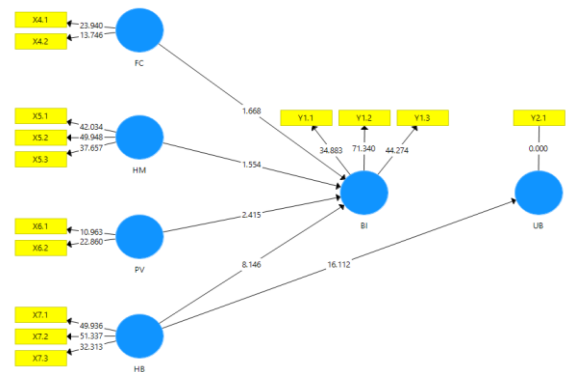


Figure 4. Outer Model Evaluation (Female)

The following are the results of T-Statistics and path coefficient (P-Value) for latent variables for male and female respondents, which can be seen in the table below.

Table 8. Hypothesis Test (Male)

Hypothesis	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
X4 -> Y1	0,056	0,477	0,634
X5 -> Y1	0,077	4,190	0,000
X6 -> Y1	0,063	2,668	0,008
X7 -> Y1	0,060	7,032	0,000
X7 -> Y2	0,067	7,565	0,000

Table 9. Hypothesis Test (Female)

Hypothesis	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
X4 -> Y1	0,059	1,668	0,096
X5 -> Y1	0,078	1,554	0,121
X6 -> Y1	0,072	2,415	0,016
X7 -> Y1	0,065	8,146	0,000
X7 -> Y2	0,041	16,112	0,000

The information presented in Figures 3 and 4 and Tables 8 and 9 above indicates that hypotheses H10b and H10c meet the criteria and can be accepted.

4. Hypothesis Test for Experience as Moderator

In this study, the experience variable is divided into two groups: respondents with less than 2 years of usage are categorized as less experienced, while those with more than 2 years of usage are categorized as experienced. The previously tested respondents will be separated into two groups: 267 less experienced respondents and 121 experienced respondents, who will be tested using different models.

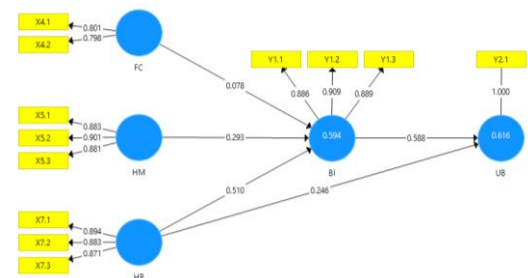


Figure 5. Outer Model Evaluation (Less than 2 years experience)

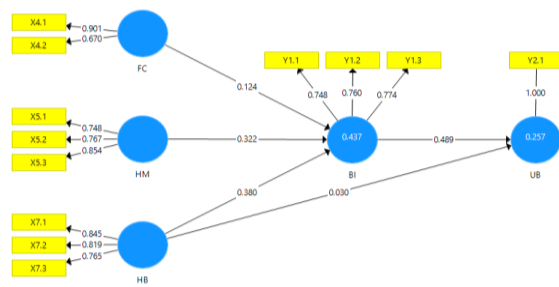


Figure 6. Outer Model Evaluation (More than 2 years experience)

The following are the results of T-Statistics and path coefficient (P-Value) for latent variables in the less experienced group (less than 2 years) and the experienced group (more than 2 years), which can be seen in the table below.

Table 10. Hypothesis Test (less than 2 years experience)

Hipotesis	Standard Deviation (STDEV)	T Statistics ((O/STDEV))	P Values
X4 → Y1	0,054	1,444	0,149
X5 → Y1	0,068	4,323	0,000
X7 → Y1	0,060	8,492	0,000
X7 → Y2	0,071	3,486	0,001
Y1 → Y2	0,064	9,161	0,000

Table 11. Hypothesis Test (more than 2 years experience)

Hipotesis	Standard Deviation (STDEV)	T Statistics ((O/STDEV))	P Values
X4 → Y1	0,084	1,473	0,141
X5 → Y1	0,084	3,820	0,000
X7 → Y1	0,081	4,711	0,000
X7 → Y2	0,092	0,326	0,745
Y1 → Y2	0,080	6,107	0,000

The information presented in Figures 5 and 6 and Tables 10 and 11 above indicates that hypothesis H11a meets the criteria and can be accepted.

3. 2 Discussion

H8: Anonymity will have a positive effect on Behavioral Intention toward AI Chatbot usage among university students in Medan.

The hypothesis test results show that anonymity (X8) has a T-Statistics value of 8.989 > 1.960, a P-Value of 0.000 < 0.05, and an original sample value of 0.412, indicating that this hypothesis is accepted. Therefore, it can be concluded that the anonymity variable (X8) has a positive and significant effect on Behavioral Intention (Y1) toward AI Chatbot usage among university students in Medan.

H9: Behavioral Intention will have a positive effect on AI Chatbot Usage Behavior among university students in Medan.

The hypothesis test results show that Behavioral Intention (Y1) has a T-Statistics value of 11.46 > 1.960, a P-Value of 0.000 < 0.05, and an original sample value of 0.595, indicating that this hypothesis is accepted. Therefore, it can be concluded that the Behavioral Intention variable (Y1) has a positive and

significant effect on Usage Behavior (Y2) of AI Chatbots among university students in Medan.

H10b: Gender moderates the relationship between Hedonic Motivation and Behavioral Intention toward AI Chatbot usage among university students in Medan, where male users show a stronger moderating effect than female users.

The hypothesis test results show that male and female groups have a T-Statistics value of 4.190 > 1.554, a P-Value of 0.000 < 0.121, and an original sample value of 0.322 > 0.121. This indicates that the hypothesis in this category is accepted. Therefore, it can be concluded that gender moderates the relationship between Hedonic Motivation (X5) and Behavioral Intention (Y1) toward AI Chatbot usage among university students in Medan, where male users exhibit a stronger moderating effect than female users.

H10c: Gender moderates the relationship between Price Value and Behavioral Intention toward AI Chatbot usage among university students in Medan, where male users show a stronger moderating effect than female users.

The hypothesis test results show that male and female groups have a T-Statistics value of 2.668 > 2.415, a P-Value of 0.008 < 0.016, and an original sample value of 0.169 < 0.173. This indicates that the hypothesis in this category is accepted. Therefore, it can be concluded that gender moderates the relationship between Price Value (X6) and Behavioral Intention (Y1) toward AI Chatbot usage among university students in Medan, where male users exhibit a stronger moderating effect than female users.

H11a: Experience moderates the relationship between Facilitating Conditions and Behavioral Intention toward AI Chatbot usage among university students in Medan, where more experienced users show a stronger moderating effect than less experienced users.

The hypothesis test results show that the less experienced and more experienced groups have a T-Statistics value of 1.444 < 1.473, a P-Value of 0.149 > 0.141, and an original sample value of 0.078 < 0.124. This indicates that the hypothesis in this category is accepted. Therefore, it can be concluded that experience moderates the relationship between Facilitating Conditions (X4) and Behavioral Intention (Y1) toward AI Chatbot usage among university students in Medan, where more experienced users exhibit a stronger moderating effect than less experienced users.

4. CONCLUSION

This study explores AI Chatbot usage among university students in Medan using the UTAUT2 model. It highlights how chatbot anonymity

influences students' behavioral intentions by making them feel more comfortable asking questions without fear of judgment. The research also finds that price value and habit significantly impact chatbot usage, as students perceive free AI Chatbots as valuable and incorporate them into their daily routines. While habit and behavioral intention positively affect actual chatbot usage, factors like performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation do not significantly influence behavioral intention. Demographic factors such as gender and experience moderate chatbot usage. Men are more influenced by hedonic motivation and price value, while experienced users show stronger effects from facilitating conditions, and less experienced users rely more on habit and hedonic motivation. Overall, the study suggests that developers should continue offering free AI Chatbots, focus on habit-forming strategies, and enhance features to better support students' learning. The research emphasizes how chatbot anonymity helps students overcome privacy concerns and ask academic and non-academic questions more freely.

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