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Evaluation Virtual Assistant Chatbot Acceptance with an Unified Technology Acceptance and Use of Technology-Based Model

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Abstract

The virtual assistant chatbot in the MyTelkomsel application is a company's effort to achieve goals and improve business performance. Chatbot as a virtual assistant has advantages and disadvantages. Evaluating user acceptance of the Virtual Assistant Chatbot in the MyTelkomsel application is important to overcome so that users do not switch to using other products. One of the models used to evaluate user acceptance of information systems is the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT is able to explain how the use of technology can be influenced by individual differences in use. The conclusion of this study is that the variables that influence the acceptance of the use of virtual assistant chatbots in the MyTelkomsel application consist of the greatest influence is shown in the effect of social influence on Behavioural intention with a value of 5,768. Then the second largest influence is the trust variable on behavioural intention with a value of 5,220. Meanwhile, the variable that has the smallest influence on behavioural intention is effort expectancy with a value of 5,134.

Keywords: Virtual Assistant, Chatbot, MyTelkomsel, UTAUT

1. INTRODUCTION

Telkomsel is a cellular operator that has a large market share and is in great demand by customers in Indonesia because Telkomsel has a very wide coverage network throughout Indonesia, including in rural areas [1]. Telkomsel often holds attractive promotional programs, such as discount offers, credit bonuses, and prizes for loyal customers [2]. In addition, Telkomsel has also developed a digital service application known as MyTelkomsel. The MyTelkomsel application is designed to meet the demands of digital technology development and provide users with ease and convenience in accessing various Telkomsel services and information. In addition, this application focuses on the principle of costumer-centricity, which means a marketing approach tailored to user needs [3]. Through MyTelkomsel, customers can fulfill all their needs, such as subscribing to internet

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packages, checking credit balance, redeeming Telkomsel points, checking remaining quota, and paying for Indihome and Vidio subscriptions. MyTelkomsel App also integrates digital payments such as LinkAja, GoPay, Shopeepay, OVO, and DANA [4].

The MyTelkomsel application continues to improve its performance by utilizing Artificial Intelligence in the virtual assistant service on the MyTelkomsel application. Virtual assistants basically consist of a series of Natural Language Processing-based programming languages that allow users to interact verbally and receive responses from applications, similar to the way individuals interact with other individuals [5]. Veronika is a virtual assistant intended specifically for Telkomsel customers. Telkomsel uses chatbot technology and artificial intelligence in building Veronika[6].The existence of Telkomsel's chatbot virtual assistant helps deal with problems that often occur in conventional customer service [7] such as responses to customer complaints that take a long time to process and the default answers given.

The utilisation of chatbots in the telecommunications industry has become a growing trend with a significant impact on customer service and user experience. Behind the advantages provided by chatbots, there are disadvantages of chatbots as virtual assistants, namely their limited ability to understand human language [8], and the information obtained from chatbots is less reliable [9]. The Zendesk 2020 Customer Experience Trends report highlights the importance of first impressions with chatbots. According to the report, 60% of customers believe that their initial experience with a chatbot must be positive, or they will not use it again [10]. Salesforce in 2021 stated an increased reliance on chatbots in customer service, as 69% of customers prefer to use chatbots for quick communication with companies. However, only 23% of those customers were satisfied with their chatbot experience [11].

From these statistics, it is known that it is necessary to evaluate the MyTelkomsel virtual assistant chatbot to continuously improve chatbot performance and ensure that the chatbot can effectively meet user expectations so that users do not switch to using other products. One of the models used to evaluate user acceptance of information systems is the Unified Theory of Acceptance and Use of Technology (UTAUT) created by Venkatesh et al. in 2003. The advantage of using UTAUT lies in its ability to explain the impact of individual differences on differences in technology use. Through explaining the relationship between UTAUT factors, such as performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention, UTAUT is able to explain how technology use can be influenced by differences in individuals who use it, both in terms of perceived benefits, ease of use, and intention to use [12]. Research on evaluating of virtual assistant chatbots acceptance using the Unified Technology Acceptance and Use of Technology-Based Model is important for

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companies to understand user behavior in accepting virtual assistant chatbots through the variables contained in the conceptual model and to improve technology implementation strategies.

2. METHODS

2.1. Conceptual Model

The conceptual model used in evaluating user acceptance of the virtual assistant chatbot on the MyTelkomsel application is adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) model used by Sanchez & Albesa, 2023 [13]. The conceptual model used is as in Figure 1.

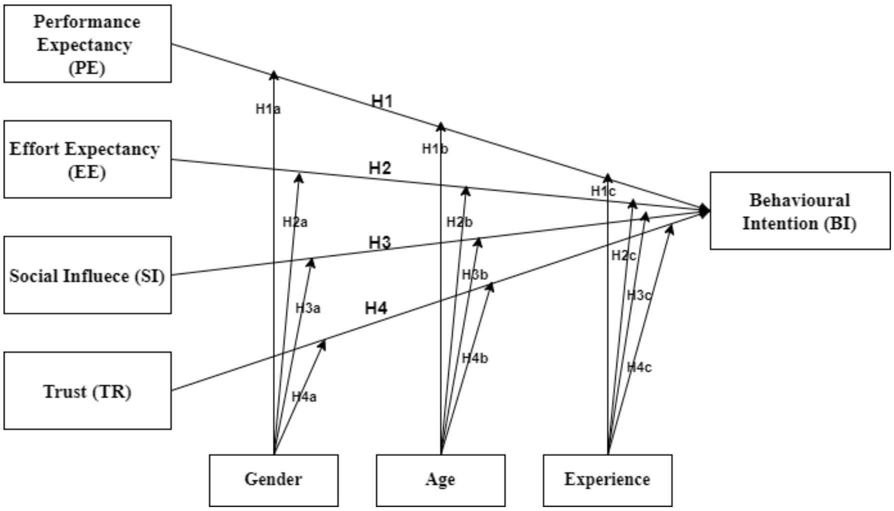

Figure 1. Research Model

2.2. Research Hypothesis

With the conceptual model described, the hypotheses in this study are as follows:

- H1: Performance Expectancy (PE) affects Behavioural Intention to use a virtual assistant chatbot on the MyTelkomsel application
- H1a: Gender moderates the effect of Performance Expectancy (PE) on Behavioural Intention
- H1b: Age moderates the effect of Performance Expectancy (PE) on Behavioural Intention
- H1c: Experience moderates the effect of Performance Expectancy (PE) on Behavioural Intention
- H2: Effort Expectancy (EE) influences Behavioural Intention to use a virtual assistant chatbot on the MyTelkomsel application

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H2a: Gender moderates the effect of Effort Expectancy (EE) on Behavioural Intention
H2b: Age moderates the effect of Effort Expectancy (EE) on Behavioural Intention
H2c: Experience moderates the effect of Effort Expectancy (EE) on Behavioural Intention.
H3: Social Influence (SI) influences Behavioural Intention to use a virtual assistant chatbot on the MyTelkomsel application.
H3a: Gender moderates the influence of Social Influence (SI) on Behavioural Intention
H3b: Age moderates the influence of Social Influence (SI) on Behavioural Intention
H3c: Experience moderates the influence of Social Influence (SI) on Behavioural Intention
H4: Trust (TR) influences Behavioural Intention to use a virtual assistant chatbot on the MyTelkomsel application
H4a: Gender moderates the effect of Trust (TR) on Behavioural Intention
H4b: Age moderates the effect of Trust (TR) on Behavioural Intention
H4c: Experience moderates the effect of Trust (TR) on Behavioural Intention

2.3. Population and Sample

The population in this study are Telkomsel operator users in Indonesia. Based on data from GoodStats, the number of Telkomsel mobile operator users in Indonesia until January 2023 reached 156 million users [14]. The number of samples is determined using the Slovin formula with an error rate of 5%. This error rate was chosen because based on studies, confirmatory research can use an error rate of 5%. The sample size calculation in this study is use Equation 1.

$$n = \frac{N}{1+Ne^2} \tag{1}$$

Description: n = Number of samples, N = Total population, e = Confidence interval / error 5% (0.05), Then:

$$n = \frac{156.000.000}{1+(156.000.000.(0{,}05)^2)}$$

$$n = \frac{156.000.000}{1+390.000}$$

$$n = \frac{156.000.000}{390.001}$$

$$n = 399{,}998$$

$$n = 400 \text{ Respondants}$$

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Based on calculations using the Slovin formula, the number of respondents needed in this research was 400 respondents.

2.4. Research Instruments

Table 1. Research Instrumen

No	Variable	Item	Question Variabel	Source
1	Performance Expectancy	PE1	The virtual assistant chatbot on the MyTelkomsel app helps me get the information I need more quickly	[15]
		PE2	Virtual assistant chatbot in the MyTelkomsel application makes it easy to determine decisions to be made in purchasing Telkomsel internet packages.	[15]
		PE3	The virtual assistant chatbot on MyTelkomsel app helps solve my network, connectivity, SIM card, credit and telkomsel quota package problems faster.	[16]
		PE4	Virtual assistant chatbot on MyTelkomsel app makes dealing with Telkomsel company easier.	[16]
		PE5	I feel the benefits of using MyTelkomsel virtual assistant chatbot	[15]
2	Effort Expectancy	EE1	Virtual assistant chatbot on MyTelkomsel app is easy to learn	[15]
		EE2	Virtual assistant chatbot on MyTelkomsel app is easy to use	[15]
		EE3	Interaction with MyTelkomsel virtual assistant chatbot is easy to understand	[15]
		EE4	I can easily access MyTelkomsel virtual assistant	[15]

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			chatbot	
3	Social Influence	SI1	My closest people influence me to use MyTelkomsel virtual assistant chatbot.	[15]
		SI2	Someone important to me encouraged me to use MyTelkomsel's virtual assistant chatbot.	[15]
		SI3	I know other people who use MyTelkomsel virtual assistant chatbot	[16]
4	Trust	TR1	I feel that MyTelkomsel virtual assistant chatbot is reliable	[17]
		TR2	The MyTelkomsel virtual assistant chatbot is one of the right solutions from the company to provide convenience for customers.	[17]
		TR3	I believe MyTelkomsel virtual assistant chatbot is safe to use	[17]
5	Behavioral Intention	BI1	I intend to use MyTelkomsel virtual assistant chatbot to answer questions related to Telkomsel operator.	[15]
		BI2	I will use a chatbot as a virtual assistant in operating the MyTelkomsel app.	[15]
		BI3	I plan to use MyTelkomsel virtual assistant chatbot in the future before coming directly to Grapari Telkomsel.	[15]

2.5. Data Processing and Analysis

This study uses statistical analysis techniques as a data analysis method using smart PLS software to process data. The data needed in this study were obtained from distributing questionnaires online using the Google Form platform. The

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stages of data analysis carried out consist of analysis of respondent demographic data, inferential analysis consisting of outer model, inner model, and hypothesis testing.

1) Respondent Demographics
   Demographic data analysis helps to describe the characteristics of research respondents, (such as age, gender, and experience) and helps to identify variables that can affect the results of the research.
2) Outer Model
   Outer model analysis includes validity and reliability tests. The validity test is used to measure the variable value of the indicator whether it is feasible or not by looking at the convergent validity and discriminant validity values. Reliability test is carried out to measure consistency in statement items arranged on the questionnaire looking at composite reliability and Cronbach's alpha values.
3) Inner Model
   Inner model analysis is carried out to predict the relationship between latent variables. can be known by looking at the R-square, Q-square values.
4) Hypotesis Testing
   This hypothesis testing was carried out using the bootstrapping method. Bootsrapping is used to obtain model parameter estimates, such as path coefficients, factor loadings, and average variance explained, T statistics, P values.

3. RESULTS AND DISCUSSION

3.1. Respondent Demographics

Demographic data of respondents in this study consisted of gender and age, in addition, data regarding the length of use of the application was also added. This demographic data is used to find out background and additional information on the research.

1) Gender Characteristics
The gender characteristics of the research respondents can be seen in table 2.

Table 2. Gender of Respondents

Gender	Total	Percentage
Female	297	74.25%
Male	103	25.75%
Total	400	100%

Table 2 shows the gender distribution of respondents in this study. Of the 400 respondents, it is known that there are more female respondents with a total of

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297 with a percentage of 74.25%, then 103 male respondents with a percentage of 25.75%. The gender distribution of respondents may provide additional insight into how different gender groups respond to or accept chatbot technology. Women may favour more friendly and empathetic interactions, while men may be more inclined to seek information directly without the need for overly personalised interactions.

2) Age Characteristics
The age characteristics of the research respondents can be seen in Table 2.

Table 3. Age of Respondents

Age Range	Jumlah	Percentage
17-29 years old	291	72.75%
30-44 years old	109	27.25%
Total	400	100%

Based on table 3, it can be seen that of the 400 respondents in this study, the majority were aged 17-29 years with a total percentage of 72.75%, namely 291 respondents. Then respondents aged 31-44 years have a presentation of 27.25%, namely 109 respondents. The 17-29 age group represents Generation Z, born between 1995 and 2009. They benefit from the rapid advancement of technology and the internet. The 30-44 age group represents generation Y or the millennial generation born between 1980 and 1994. The difference between generation Y and generation Z who were respondents in this study was 182 people more in generation Z.

3) Characteristics of Length of Application Use
The characteristics of the length of use of the application from research respondents can be seen in the following Table 4.

Table 4. Length of Application Use

Length of Use	Total	Percentage
Less than 1 years	59	14.75%
1-5 years	225	56.25%
More than 5 years	116	29%
Total	400	100%

Table 4 shows that of the 400 research respondents, 59 respondents with a percentage of 14.75% have used the application for less than 1 year, 225 respondents with a percentage of 56.25% have used the application for 1-5 years, and 116 respondents with a presentation of 29% have used more than 5 years. Based on the long experience of using the application, the respondents in this study were the most users of the application for 1-5 years as many as 225

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respondents and the least respondents were application users of less than 1 year which only consisted of 59 respondents.

3.2. Outer Model

In this study, the outer model measurement was carried out on the data that had been distributed, namely 400 respondents who were chatbot users on the MyTelkomsel application where the analysis process was carried out using SmartPLS 4 software.

1) Convergent Validity

Convergent Validity in SmartPLS software can be seen in the outer loading value of each indicator and the average variance extracted (AVE). The outer loading value used as a validity requirement must be above 0.70 and the average variance extracted (AVE) must be above 0.50. The outer loading value must be ≥ 0.5 on a variable in order to be considered significant. Table 5 below shows the outer loading results of each indicator.

Table 5. Outer Loading

	BI	EE	PE	SI	TR
BI1	0,889				
BI2	0,879				
BI3	0,845				
EE1		0,869			
EE2		0,864			
EE3		0,863			
EE4		0,836			
PE1			0,813		
PE2			0,800		
PE3			0,797		
PE4			0,805		
PE5			0,797		
SI1				0,867	
SI2				0,880	
SI3				0,883	
TR1					0,821
TR2					0,845
TR3					0,849

From table 5, it can be seen that the outer loading value of the indicators of each variable has a value of more than 0.7. So it can be interpreted that all indicators of the variables have met the requirements of convergent validity because the outer loading value> 0.7.In addition to evaluating the outer loading value, the

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Average Variance Extracted (AVE) value is also calculated. The AVE value is shown in Table 6.

Table 6. Average Variance Extracted (AVE) Value

Variable	Average variance extracted (AVE)
BI	0,759
EE	0,736
PE	0,644
SI	0,768
TR	0,703

Based on Table 6, it can be seen that all variables have an AVE value> 0.5. So based on the results of the outer loading and AVE values that have met the requirements, convergent validity has been fulfilled.

2) Discriminant Validity

Discriminant validity aims to measure the extent to which a construct is truly different or varies from other constructs. Discriminant validity can be evaluated through Heterotrait-monotrait ratio (HTMT), Fornell-Larcker and cross loading.

Table 7. Heterotrait-monotrait ratio (HTMT)

Variable	BI	EE	PE	SI	TR
BI					
EE	0,864				
PE	0,760	0,822			
SI	0,786	0,710	0,589		
TR	0,881	0,893	0,888	0,687	

Table 7 shows the results of the calculation of the Heterotrait-monotrait ratio (HTMT) for each variable have a value of less than 0.90 so that the criteria for discriminant validity with the Heterotrait-monotrait ratio (HTMT) approach are met.

Table 8. Fornell-Larcker Criterion

Variable	BI	EE	PE	SI	TR
BI	**0,871**				
EE	0,746	**0,858**			
PE	0,650	0,717	**0,803**		
SI	0,667	0,616	0,507	**0,877**	
TR	0,719	0,744	0,734	0,567	**0,839**

Table 8 above shows that the Fornell-Larcker Criterion value for each independent variable has a value greater than the correlation between

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independent variables in the same column, so the criteria for discriminant validity with the Fornell-Larcker Criterion approach have been met.

Table 9. Cross Loading

	BI	EE	PE	SI	TR
BI1	**0,889**	0,619	0,556	0,590	0,616
BI2	**0,879**	0,707	0,575	0,629	0,636
BI3	**0,845**	0,618	0,567	0,519	0,628
EE1	0,649	**0,869**	0,582	0,539	0,646
EE2	0,662	**0,864**	0,626	0,560	0,611
EE3	0,640	**0,863**	0,625	0,530	0,658
EE4	0,607	**0,836**	0,630	0,482	0,641
PE1	0,500	0,572	**0,813**	0,369	0,581
PE2	0,584	0,597	**0,800**	0,466	0,590
PE3	0,506	0,537	**0,797**	0,389	0,590
PE4	0,524	0,601	**0,805**	0,397	0,630
PE5	0,484	0,565	**0,797**	0,402	0,549
SI1	0,561	0,496	0,431	**0,867**	0,464
SI2	0,586	0,553	0,450	**0,880**	0,501
SI3	0,606	0,568	0,450	**0,883**	0,524
TR1	0,633	0,611	0,579	0,550	**0,821**
TR2	0,573	0,610	0,608	0,381	**0,845**
TR3	0,600	0,650	0,659	0,486	**0,849**

Table 9 shows the results of the calculation of cross loading, where the criterion for the cross loading value to be accepted is that the value of an indicator must have a value greater than the cross loading of indicators on other variables. In the table above, the value of all cross loading indicators has met these requirements, so the criteria for discriminant validity with the cross loading approach are met.

3) Reliability
Composite reliability is carried out to test the reliability consistency of indicators by looking at the composite reliability and Cronbach's alpha values. The composite reliability and Cronbach's alpha values must be> 0.7 to meet the reliability consistency standards. The reliability value in the study can be seen in the following table.

Table 10. Composite Reliability dan Cronbach's Alpha Value

Variable	Cronbach's alpha	Composite reliability (rho_c)	Desc
Behavioural Intention	0,841	0,904	Accepted

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Variable	Cronbach's alpha	Composite reliability (rho_c)	Desc
Effort Expectancy	0,881	0,918	Accepted
Peformance Expectancy	0,862	0,900	Accepted
Social Influence	0,849	0,909	Accepted
Trust	0,789	0,877	Accepted

Based on Table 10, it can be seen that the composite reliability and Cronbach's alpha of each variable have a value> 0.7. So it can be interpreted that all variables have met the reliability requirements.

3.3. Inner Model

Inner model testing is carried out to describe the relationship between latent variables and to test hypotheses between constructions in the conceptual model [18].

1) Variance Inflation Factor (VIF)
Based on the criteria of Diamantopoulos and Siguaw if the value of VIF is less than 5, it can be confirmed that there is no multicollinearity problem. The results of the VIF calculation can be seen in Table 11.

Table 11. Multicollinearity Variance Inflation Factor (VIF) Test

Variable	VIF
BI1	2,261
BI2	2,030
BI3	1,824
EE1	2,359
EE2	2,251
EE3	2,291
EE4	2,040
PE1	1,975
PE2	1,762
PE3	1,847
PE4	1,903
PE5	1,889
SI1	2,009
SI2	2,107
SI3	2,083
TR1	1,500
TR2	1,804
TR3	1,781

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Based on Table 11, it is known that the VIF value of each variable has a value <5. So it can be interpreted that there is no indication of multicollinearity between variables in this study.

2) R-square
The R-square value explains the amount of variability in endogenous variables that can be explained by exogenous variables. The results of the R-square calculation are shown in Table 12.

Table 12. R-square Value

Variable	R-Square
Behavioural Intention (BI)	0,668

Based on Table 12, it can be seen that the effect of perfoemance expectancy, effort expectancy, social influence and trust variables on behavioral intention variables is 0.668. This value includes a moderate effect. So it can be interpreted that the variability of the behavioral intention construct is 66.8%, while the remaining 33.2% is explained by other variables outside the model.

3) Q-square
The Q-square value can be used as another way to assess whether the model has good predictive relevance. Table 13 shows the results of the Q-square calculation.

Table 13. Q-*square* Value

Variable	Q-Square
Behavioural Intention (BI)	0,658

Based on Table 13, it can be seen that the behavioral intention variable has a Q-square value of 0.658, which is more than 0. So it can be interpreted that the model has good predictive relevance.

3.4. Hypothesis Testing

Hypothesis testing was carried out using SmartPLS 4.1.0.2 software with the bootstrapping method. The results of hypothesis testing using bootstrapping can be seen in Figure 2.

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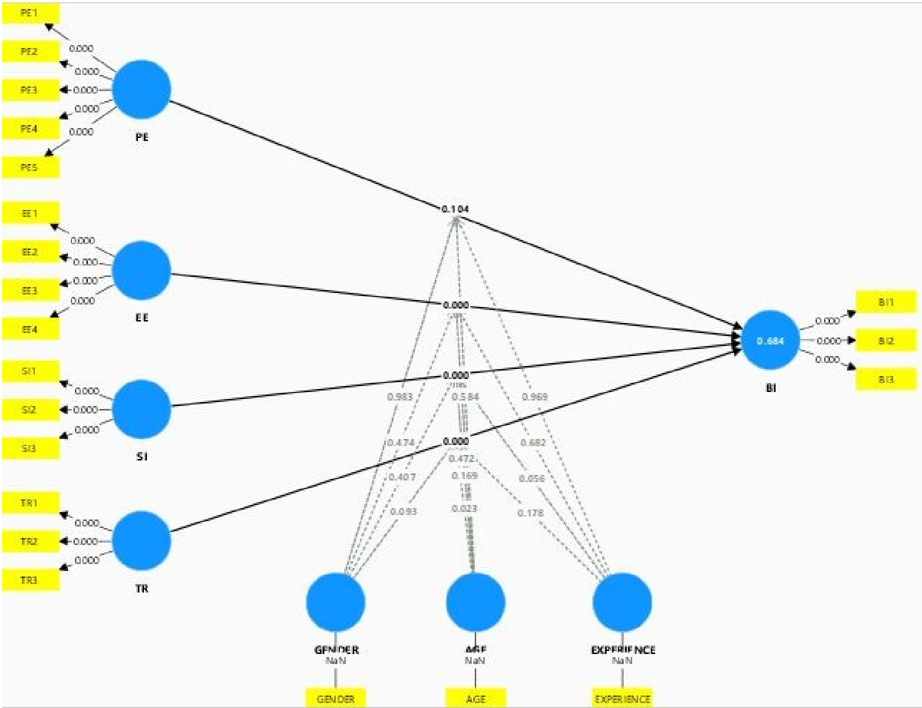

Figure 2. Bootstrapping Results

Based on Figure 2, the results of the model hypothesis test can be seen from the path coefficient value. Where if the p value is less than the significant value, namely 0.05, it shows significance, which means that the hypothesis is accepted. The results of hypothesis testing are shown in Table 14.

Tabel 14. Hypothesis Test Results

	Hypothesis	Original sample	Mean	STD	T statistics	P values	Desc
PE -> BI	H1	0,091	0,091	0,071	1,284	0,199	Not Accepted
GENDER x PE -> BI	H1a	0,007	0,009	0,054	0,137	0,891	Not Accepted
AGE x PE -> BI	H1b	0,073	0,076	0,098	0,740	0,459	Not Accepted
EXPERIENCE x PE -> BI	H1c	-0,010	-0,015	0,088	0,113	0,910	Not Accepted
EE -> BI	H2	0,313	0,307	0,061	5,134	0,000	**Accepted**
GENDER x EE -> BI	H2a	-0,029	-0,029	0,061	0,483	0,629	Not Accepted
AGE x EE -> BI	H2b	-0,128	-0,134	0,078	1,638	0,102	Not Accepted
EXPERIENCE x EE -> BI	H2c	0,037	0,038	0,083	0,439	0,661	Not Accepted
SI -> BI	H3	0,282	0,292	0,049	5,768	0,000	**Accepted**
GENDER x SI -> BI	H3a	-0,046	-0,044	0,046	0,985	0,324	Not Accepted
AGE x SI -> BI	H3b	0,012	0,020	0,054	0,230	0,818	Not Accepted
EXPERIENCE x SI -> BI	H3c	0,046	0,047	0,049	0,946	0,344	Not

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							Accepted
TR -> BI	H4	0,272	0,268	0,052	5,220	0,000	**Accepted**
GENDER x TR -> BI	H4a	0,073	0,067	0,051	1,413	0,158	Not Accepted
AGE x TR -> BI	H4b	0,160	0,149	0,082	1,941	0,052	Not Accepted
EXPERIENCE x TR -> BI	H4c	-0,073	-0,066	0,080	0,914	0,361	Not Accepted

3.5. Disscussion

The results show that although the impact of performance expectancy (PE) on the adoption of new technologies such as Business Intelligence (BI) tends to be positive, it is not statistically significant. This is consistent with previous findings, for example in the context of m-banking services [19]. However, Effort Expectancy (EE) was found to have a significant and positive impact on intention to use the technology. This is in line with the revised literature and previous findings related to digital banking [20], and consumer adoption of chatbots [21]. The variable that most strongly influenced behavioral intention was social influence (SI). This finding is consistent with previous research in the context of consumer acceptance of chatbots[22].

Trust (TR) was also shown to have a significant and positive impact on behavioral intention, in line with expectations, given the intrinsic trust-dependent nature of the insurance business, as well as its relevance in the acceptance of robotic technologies [23]. Meanwhile, the moderating impact of gender, age, and experience turned out to be insignificant, contrary to the initial assumption of the UTAUT framework [15].

The variables that show statistical significance in the research sample are effort expectation, social influence, and trust. Social influence proved to be the most relevant factor in explaining behavioral intention with a value of 5,768. Then trust on behavioral intention with a value of 5,220. effort expectancy on behavioral intention with a value of 5,134. So that the accepted hypothesis contained in this study are hypothesis 2, hypothesis 3, and hypothesis 4.

4. CONCLUSION

The variables that influence the acceptance of using virtual assistant chatbots in the MyTelkomsel application consist of Effort Expectancy, Social Influence, and Trust, each of which has a significant effect (P values <0.05) on the intention to use virtual assistant chatbots in the MyTelkomsel application. The variable with the greatest influence is shown in the effect of social influence on Behavioural intention with a value of 5,768. Then the second largest influence is the trust variable on behavioural intention with a value of 5,220. Meanwhile, the variable that has the smallest influence on behavioural intention is effort expectancy with

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a value of 5,134. So that the accepted hypothesis in this study are hypothesis 2, hypothesis 3, and hypothesis 4. Based on the findings from the research results, steps that companies can take to increase user acceptance of virtual assistant chatbots in the MyTelkomsel application include involving influencers in promoting chatbots, maintaining chatbot quality by ensuring that chatbots are able to provide fast and precise responses to user questions, and continuously improving chatbot performance. Suggestions for future research could expand the conceptual model by including additional relevant variables, such as service quality, user satisfaction, or technical factors that affect the performance of virtual assistant chatbots. In addition, it can also conduct in-depth qualitative research to better understand the factors that influence user acceptance and experience of virtual assistant chatbots. This can be done through in-depth interviews, case studies, or participatory observation.

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