Factors Influence Satisfaction and Continuance Intention of Chatbot Users

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Abstract. The pandemic has led to increased penetration in the digitalization sector, one of which is online shopping. The increase in online shopping activities poses challenges for businesses serving consumers, especially customer service. In this situation, chatbots can be a solution to provide better service to consumers. Satisfaction and continuance intention of a chatbot is important variables because they relate to several desired outcomes by businesses. Information System Success (ISS) Model, Technology Acceptance Model (TAM), and Expectation-Confirmation Model (ECM) are combined. Using the SEM-PLS method on 210 respondents' data collected concluded that satisfaction was significantly influenced by confirmation of expectations, perceived ease of use and enjoyment. Meanwhile, satisfaction, perceived enjoyment and usefulness significantly influence continuance intention. This research contributes in several ways related to the understanding of chatbot users in Indonesia and how to improve the experience based on the findings.

Keywords: Chatbot · Continuance Intention · Satisfaction · SEM-PLS

1 Introduction

The covid-19 pandemic disrupted many things, especially things related to interpersonal interaction. Limiting direct physical interaction encourages people to look for safer alternatives so that new habits emerge, some behaviors are strengthened, and some behaviors need to be abandoned. The most common topic in dealing with this pandemic condition is how digitization is accelerating in various aspects of human life, including how to purchase things [1].

During the outbreak, there has been a rise in online shopping. People's views and shopping patterns tend to shift with increased safety concerns. McKinsey [2] reports 2–5 times growth in e-commerce due to the pandemic, as the platform is growing rapidly. E-commerce penetration has become more effective and will still increase even after the pandemic due to the consumer's convenience and significant adaptation of digital payment. Not only limited to e-commerce, other virtual transactions like restaurant delivery, online grocery shopping, online education, and telemedicine also get a significant increase in demand during pandemic conditions. Online purchasing has emerged as a viable option for resolving business interruptions in various industries. For continued

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development to support online purchase operations, a solid online communication system with clients would be a major issue, as increasing demand trends become a challenge for businesses to maintain communication with customers [3].

Online retailers can attract more customers and increase the value of their stores by providing a positive buying experience. A more advanced and convenient communication form with clients has become a new requirement in online business. Many businesses try to improve consumer happiness in several ways, one of which is providing excellent service [4]. Unlike offline channels, online channels are not bound by operation time. Customers have the flexibility to access the channel all day. Even though most e-commerce is well-designed to provide information related to the product, many customers still contact customer service to ask for the product info or the availability. Customer service availability could become an important factor for businesses to make successful sales. A reset and renewal of the system can be done to meet the need for a speedier response with little human participation. Chatbots may be able to help with the present scenario.

If well-systematized, chatbots can produce good results [5]. It will result in the efficient use of resources and reduce costs. However, it is hard to develop a human-like chatbot that feels connected and has empathy, which can lead to discomfort experience for the customer. Inability to solve complex problems, privacy, inconsistent performance, and several issues faced by chatbots cause doubts from business people to use them. [6, 10].

The research found that human interaction is preferable for 87% of respondents instead of a chatbot [6]. Human customer service is still more favorable than the chatbot, especially related to understanding a complex situation. The chatbot will lead to smaller purchases when the expectation of information and empathy cannot be fulfilled [7].

Satisfaction and continuance intention from the user are important to pay attention to, as they are related to several expected outputs. Altukar [11] mentioned that brand loyalty is caused by satisfaction. While research from [12] shows that continuance intention is strongly related to retention. While numerous ideas and data support the link between satisfaction and continuance intention, research into additional elements that impact both variables has shown a variety of outcomes [13, 15].

2 Style Palette

2.1 Chatbot

Chatbots are artificial intelligence (AI)-based systems that converse with humans via text or other forms of communication [16, 17]. Although the most popular chatbots are from the top technological firms, such as Google Assistant and Siri from Apple, chatbots are already being used in various enterprises because it needs less cost and has better accessibility. According to Forbes [6], 80 percent of businesses have either used or are planning to use chatbots to communicate with their consumers since this technology has the potential to assist businesses in effectively delivering nonstop support to clients, especially given the price. One of the most crucial components in online buying, according to Forbes [18], is a quick response to customer support. This situation compels firms to use chatbots as a solution to provide always-on customer service.

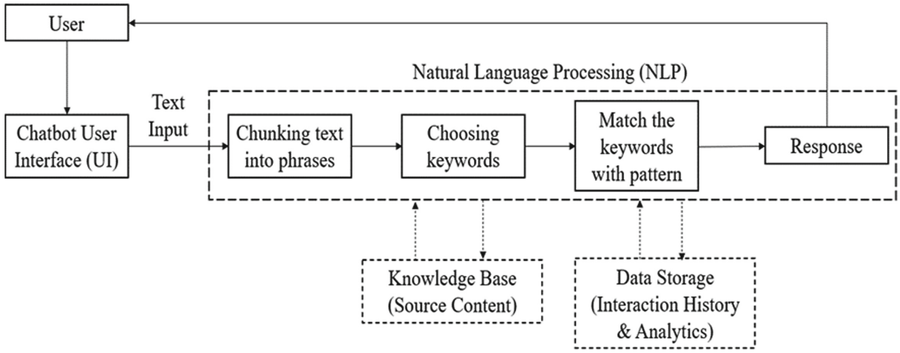

Fig. 1. Process of NLP Based Chatbot System

Ahmad et al. [19] tried to describe the chatbot system process in Fig. 1. At the beginning of the process, the chatbot should have a user interface to be accessible to the user. The user interface will be related to the messenger application where the chatbot is plugged in in this research context. After the user input the text, the chatbot will process it by chunking it into phrases, choosing the keyword then matching it with the pattern to give a proper response. In addition, to describe the system, there are three basic classifications related to the architecture of chatbots. Natural Language Processing (NLP) is the most used structure, compared with pattern match and Natural Language Understanding (NLU) as chatbot architecture, because of its learning ability. While processing the conversation, the chatbot continuously retrieves and learns by source content and analysis of historical data.

2.2 Satisfaction and Continuance Intention

Businesses consider continuance intention and satisfaction with chatbots essential since they are linked to several crucial expected outcomes. Satisfaction is linked to brand loyalty, whereas repeat order intention is highly linked to satisfaction [11, 12]. While numerous ideas and data support the link between contentment and desire to continue, research into additional elements that impact satisfaction and continuance intention has shown various outcomes [13, 15].

This research adopted the model from Ashfaq [13] as it has continuance intention and satisfaction and related factors as identical variables to investigate. In addition, to make a differentiation, this research also includes confirmation of expectation, as it is an important variable of the Expectation-Confirmation Model (ECM). As shown in Table 1, the relation between confirmation of expectation and satisfaction in the chatbot context research appears in varying results [2022]. Using this modified model with Indonesian respondents, investigating factors that influence satisfaction and continuance intention could bring new insight related to chatbot acceptance in Indonesia [21]. As Ashfaq [13] also mentioned, the results could be influenced by cultural variables and different chatbot popularity in different regions.

Table 1. Past Research of Satisfaction and Continuance Intention of Chatbot Users.

Article	Result
(Eren, B. A., 2021) [20]	Perceived trust and performance influence satisfaction of chatbot customer. Expectations have a beneficial impact on perceived performance. However, in this case, expectations do not indicate a direct effect on satisfaction. Expectations have effect on satisfaction, indirectly, explained by perceived performance. However, confirmation of expectations of a chatbot is not significantly impacted by chatbot customer expectations.
(Ashfaq, M., Yun, J., Yu, S., and Loureiro, S. M. C., 2020) [13]	Customer continuance intention to use chatbot is mainly influenced by satisfaction. Quality of service and information positively influence chatbot customer satisfaction. In comparison, continuance intention is predicted by three major variables, perceived usefulness, ease of use, and enjoyment. Perceived usefulness and ease of use on satisfaction are impacted by the need for interaction with a service employee.
(Sanny, L., Susastra,, A. C., Roberts, C., and Yusramdaleni, R., 2020) [21]	Overall, four consumer satisfaction variables drive chatbot acceptability in Indonesia: utility, brand image, personality, and simplicity of use.
(Nguyen, D. M., Chiu, Y. T., and Le, H. D., 2021) [22]	The intention of a bank customer to continue using chatbot service is affected by satisfaction, perceived usefulness, and trust as the most important variable. Quality of information, service, and system substantially influence satisfaction, perceived usefulness, and trust with the continuance intention.
(Hsiao, K. L. and Chen, C.C., 2021) [23]	Satisfaction directly impacts continuity intention, with service quality and anthropomorphism as important factor that influence satisfaction and trust.

2.3 Expectation-Confirmation Model (ECM)

This theory confirms expectation, satisfaction, perceived usefulness, and continuance intention. Bhattacherjee [15] created the Expectation-Confirmation Model (ECM) to comprehend information system continuity better. As shown in Fig. 2, satisfaction and perceived usefulness predict satisfaction, and satisfaction is predicted by confirmation of expectation and perceived usefulness. Perceived usefulness is also predicted by confirmation of expectation. Perceived usefulness and satisfaction indicate continuation intention, which is the variable pursued by most information systems [14]. If chatbot

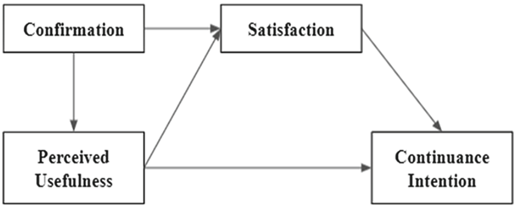

Fig. 2. Expectation-Confirmation Model

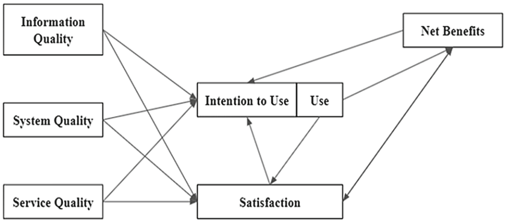

Fig. 3. Information System Success (ISS) Model

users believe that the chatbot, as a relatively new technology, is useful and can surpass expectations, users will continue to utilize chatbots.

2.4 Information System Success (ISS) Model

This model is advanced by Delone and McLean [24] as an upgrade to the prior model [25]. This model describes how the user's perceived usefulness is predicted by usage and satisfaction and satisfaction and desire to continue using the product. The new variable from the previous model is service quality. They noted that information quality and service quality are crucial criteria for an information system's success [2628], which is also true in the case of chatbots. As shown in Fig. 3, this model describes product satisfaction and intention to use are mainly determined by the quality of information, system, and service.

2.5 Technology Acceptance Model (TAM)

This model was created by Davis [29] and had the basic assumption that perceived usefulness is predicted by perceived ease of use. Both variables also impact intention to use new technology and attitude. The smoothness of the user experience bothered by unclear information, technical problems, and other variables will diminish the predicted outcome's success. Perceived enjoyment has been the subject of several past research [13, 30, 31], which have looked at how perceived ease of use and perceived enjoyment affect satisfaction and continuance intentions.

2.6 Need for Interaction with a Service Employee

As an enrichment to the explanation of satisfaction and continuance intention, Ashfaq [13] adding the need for interaction with a service employee to devote more attention

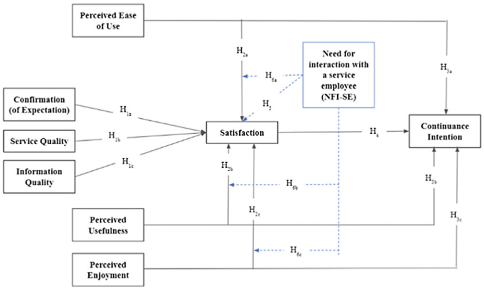

Fig. 4. Conceptual Framework

to personal trait variations. The need for interaction with a service employee acts as a mediator between perceived usefulness and perceived ease of use and predicts chatbot user satisfaction [13, 32]. If there is a greater requirement for engagement with service staff, the chatbot experience may suffer. This condition might happen if chatbots take the role of people in customer service and diminish human-to-human interaction [33].

3 Conceptual Framework and Hypothesis

Figure 4 depicts the hypotheses that underpin this research. ECM, ISS model, and TAM are all used in this framework. The structure below has been adapted from Ashfaq et al. study's [13]. As a supplement to provide a deeper result, expectation confirmation is included since it conforms with the hypothesis that satisfaction occurs from satisfied expectations [34], backed by data on the types of expectations that chatbot users have. The hypotheses are listed in Table 2.

4 Methodology

This research uses a qualitative method, conducted from May to December 2021, with a two-phase data collection period. The first phase is from 23rd to 26th July, and the second phase is from 29 November to 13 December. Data are collected using an online questionnaire. People who live in Indonesia, are between the ages of 18 and 50, and have interacted with chatbots are the focus of this study. This research involves 210 participants from a minimum sample size of 91 people due to the maximum number of arrows [35].

5 Analysis and Result

5.1 Reliability and Validity

This research uses the PLS-SEM, and it is crucial to double-check the measuring instrument's accuracy and validity. According to Hair et al. [36], indicator and composite reliability are used to assess reliability, while the convergent and discriminant validity checks the validity. SmartPLS 3.3 was used for the whole analysis.

Table 2. Hypotheses

Number	Hypotheses
H1a	Confirmation positively influences the satisfaction of chatbot users.
H1b	Service Quality positively influences the satisfaction of chatbot users.
H1c	Information Quality positively influences the satisfaction of chatbot users.
H2a	Perceived Ease of Use positively influences the satisfaction of chatbot users.
H2b	Perceived Usefulness positively influences the satisfaction of chatbot users.
H2c	Perceived Enjoyment positively influences the satisfaction of chatbot users.
H3a	Perceived Ease of Use positively influences users' continuance intention to use chatbots.
H3b	Perceived Usefulness positively influences users' continuance intention to use chatbots.
H3c	Perceived Enjoyment positively influences users' continuance intention to use chatbots.
H4	Satisfaction positively influences users' continuance intention to use chatbots.
H5	The need for interaction with a service employee negatively influences the satisfaction of chatbot users.
H6a	The need for interaction with a service employee moderates the effect of Perceived Ease of Use on satisfaction.

5.1.1 Indicator Reliability

The square of each outer loading indication yields the indicator reliability [35]. If the research is exploratory, 0.7 or higher is desirable for indication reliability, and 0.4 or higher is acceptable. Except for six items, the indicators in this questionnaire pass the criterion, as indicated in Table 3. Indicators that fail to meet the indicator reliability standard are removed from the analysis and will not be further used.

5.1.2 Composite Reliability

The internal consistency of each variable is measured by composite reliability [35]. The number must be 0.7 or greater to be approved. When the research is exploratory, however, 0.6 or higher is acceptable. As indicated in Table 4, all variables meet the composite reliability criteria.

5.1.3 Convergent Validity

Convergent validity uses AVE to determine the validity. A variable is considered legitimate when the AVE is greater than 0.5 [35]. As demonstrated in Table 5, all of the variables in this study are valid based on convergent validity.

Table 3. Indicator Reliability

Variable Name (Source)	Item Number	Factor Loadings	Indicator Reliability
Confirmation (CON) (Bhattacherjee, 2001)	1		-
SQ (Roca et al., 2006)	1	0.416	0.173
	2	0.768	0.590
	3	0.425	0.181
	4	0.578	0.334
	5	0.798	0.637
	6	0.826	0.682
IQ (Teo et al., 2008)	1	0.794	0.630
	2	0.679	0.461
	3	0.800	0.640
	4	0.816	0.666
	5	0.808	0.653
	6	0.733	0.537
	7	0.800	0.640
PEOU (Liao et al., 2007)	1	0.799	0.638
	2	0.771	0.594
	3	0.680	0.462
	4	0.719	0.517
PU (Oghuma et al., 2016)	1	0.846	0.716
	2	0.872	0.760
	3	0.874	0.764
	4	0.891	0.794
PE (Lee & Choi, 2017)	1	0.867	0.752
	2	0.884	0.781
	3	0.885	0.783
	4	0.735	0.540
	5	0.868	0.753
Satisfaction (Oghuma et al., 2016)	1	0.890	0.792

(*continued*)

Table 3. (*continued*)

Variable Name (Source)	Item Number	Factor Loadings	Indicator Reliability
	2	0.891	0.794
	3	0.827	0.684
CI (Bhattacherjee, 2001)	1	0.895	0.801
	2	0.873	0.762
	3	0.883	0.780
NFI-SE (Dabholkar & Bagozzi, 2002)	1	0.630	0.397
	2	0.533	0.284
	3	0.546	0.298
	4	0.973	0.947

Table 4. Composite Reliability

Variable	Composite Reliability
Confirmation	1
SQ	0.869
IQ	0.914
PEOU	0.831
PU	0.926
PE	0.928
Satisfaction	0.903
CI	0.914
NFI-SE	1

5.1.4 Discriminant Validity

To determine the discriminant validity, the correlations with other variables should be smaller than the square root of each variable's AVE [37]. As indicated in Table 6, discriminant validity indicates that this questionnaire is valid.

5.2 Hypothesis Testing

Bootstrapping uses 5000 subsamples after examining the measurement's reliability and validity. Expectation confirmation positively impact satisfaction, and satisfaction has a strong positive influence on continuance intention. Overall, six of fourteen hypotheses are accepted, as shown in Table 7.

The satisfaction of chatbot users is unaffected by the quality of the service or the information provided. PEOU has a positive impact on satisfaction, but no direct effect on

Table 5. Convergent Validity (AVE)

Variable	Average Variance Extracted
Confirmation	1
SQ	0.688
IQ	0.604
PEOU	0.553
PU	0.758
PE	0.722

CI. PU has a favorable impact on CI but does not affect satisfaction. PE has a considerable positive impact on both satisfaction and CI. As an independent variable, the need for interaction with a service employee has no bearing on satisfaction. In addition, it does not affect relation of satisfaction with perceived usefulness, perceived ease of use, or perceived enjoyment.

5.3 Structural Model Analysis

Hu & Bentler [38] suggest that a model can be considered a good fit when the SRMR score is not 0.08 or above. From the SmartPLS algorithm test, the SRMR score for this model is 0.063.

64.8 percent of satisfaction and 57.6 percent of CI can be explained by the factors in this model, as illustrated in Fig. 5. The main influential factors for the satisfaction of the chatbot user are confirmation of expectation (β= 0.296) and perceived ease of use (β = 0.247). The most influential factors for the continuance intention are satisfaction (β = 0.426) and perceived usefulness (β = 0.402).

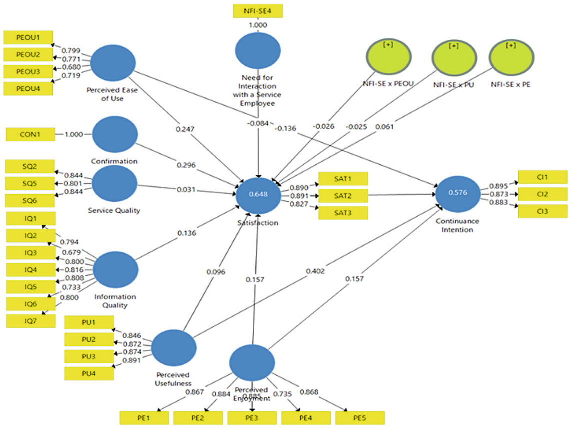

Fig. 5. Chatbot Satisfaction and Continuance Intention Model

Table 6. Discriminant Validity

	CON	CI	IQ	NFI-SE	PEOU	PE	PU	SAT	SQ
CON	1.000								
CI	0.526	0.884							
IQ	0.642	0.492	0.777						
NFI-SE	-0.176	-0.153	-0.128	1.000					
PEOU	0.506	0.506	0.672	-0.115	0.744				
PE	0.480	0.571	0.499	-0.219	0.554	0.850			
PU	0.514	0.664	0.607	-0.103	0.673	0.579	0.871		
SAT	0.664	0.677	0.660	-0.234	0.669	0.603	0.616	0.870	
SQ	0.599	0.507	0.676	-0.199	0.602	0.681	0.636	0.635	0.830

6 Discussion

As previously stated, brand loyalty is strongly linked to customer satisfaction and continuance intentions and the shopping experience and decision-making process [11, 12]. Striking for the pleasure and retention of chatbot users is vital since it aligns with the desired output of a successful business. According to the findings of this study, fulfilling users' expectations and ensuring that the chatbot is viewed as simple, useful, and enjoyable is one approach to boost satisfaction and continuance intentions.

This study's hypothesis testing results reveal that satisfaction is not affected by service and information quality. This finding contradicts various ideas and past research that identify information and service quality as significant satisfaction indicators. However, other earlier studies have also produced contradictory results [13, 15, 24]. This result might happen due to the interaction of several responder attributes.

Another contradictory finding is that the NFI-SE has no detrimental impact on satisfaction. It suggests that customers can be pleased with chatbots while still having a strong need for human connection in the form of customer support. This is possible since many customer care chatbots just manage the communication process in a simple situation. Human customer help is accessible when a complex problem arises. While chatbots are still being created to address complicated problems, combining chatbots with people in customer service is an excellent approach to please consumers efficiently [13].

Table 7. Hypothesis Testing

Hypothesis	Path	Beta	T-Value	P Values	Result
H1a	CON - > SAT	0.296	3.985	0.000	Accepted
H1b	SQ - > SAT	0.031	0.386	0.700	Rejected
H1c	IQ - > SAT	0.136	1.345	0.179	Rejected
H2a	PEOU - > SAT	0.247	3.761	0.000	Accepted
H2b	PU - > SAT	0.096	1.357	0.175	Rejected
H2c	PE - > SAT	0.157	2.795	0.005	Accepted
H3a	PEOU - > CI	-0.136	1.790	0.073	Rejected
H3b	PU - > CI	0.402	5.310	0.000	Accepted
H3c	PE - > CI	0.157	2.230	0.026	Accepted
H4	SAT - > CI	0.426	5.653	0.000	Accepted
H5	NFI-SE - > SAT	-0.084	1.942	0.052	Rejected
H6a	NFI-SE x PEOU - > SAT	-0.026	0.412	0.681	Rejected
H6b	NFI-SE x PU - > SAT	-0.025	0.354	0.723	Rejected
H6c	NFI-SE x PE - > SAT	0.061	1.050	0.294	Rejected

7 Implications

In various respects, this study contributes to the knowledge of chatbot users. First, this study adds to Ashfaq's [13] empirical evidence of chatbot users' satisfaction and continuance intention using the chatbot, which combines the ECM [15], ISS Model [24, 25], and TAM [29]. According to this research, PE and PEOU are both significant factors that positively impact satisfaction, and PU and PE are both significant elements that positively affect continuance intention. Service quality, information quality, and the necessity for interaction with a service person are criteria that do not substantially impact satisfaction. Hence this research yielded diverse results. LIKEWISE, the NFI-SE does not influence the link between PE, PEOU, and PU on satisfaction.

Second, in line with ECM [15], this research incorporates expectation confirmation as a model enrichment. Confirmation of expectations was shown to be the most influential factor in satisfaction in this study. This finding may help to explain the contradictory findings on the relationship between chatbot user satisfaction and confirmation of expectation. Third, because the study is limited, chatbot penetration has varying degrees in each nation, and county-level culture is projected to impact the outcome. This research also helps to uncover satisfaction and continuation intention elements of chatbot users in Indonesia [13].

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