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The Influence of Conversation Skills on Chatbot on Purchase Behavior in E-Commerce

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Abstract
To date, chatbots have been widely used in e-commerce as a replacement for conventional customer service agents. This study aims to analyze the influence of chatbots' conversation skills on purchasing decisions made by e-commerce users. The specific skills examined were tailored response and response variety. This study used quantitative methods with online questionnaires and involved 699 respondents who had shopped on an e-commerce website and used a chatbot feature in the application. The e-commerce platforms involved in this study were the top five used in Indonesia: Shopee, Tokopedia, BliBli, Lazada, and Bukalapak. The data collected were analyzed using the partial least squares structural equation modeling method. The results show that the conversational skills of chatbots can influence consumer shopping decisions which can increase the sales of e-commerce organizations. The results provide guidance for e-commerce platforms using chatbots to help consumers with shopping.

Keywords—Conversational Skills; Chatbot; E-Commerce; Indonesia; Purchase Behavior

Abstrak
Saat ini, chatbots telah banyak digunakan dalam e-commerce sebagai pengganti agen layanan pelanggan konvensional. Penelitian ini bertujuan untuk menganalisis pengaruh keterampilan percakapan chatbots terhadap keputusan pembelian yang dilakukan oleh pengguna e-commerce. Keterampilan khusus yang diperiksa adalah respons yang disesuaikan dan variasi respons. Penelitian ini menggunakan metode kuantitatif dengan kuesioner online dan melibatkan 699 responden yang pernah berbelanja di website e-commerce dan menggunakan fitur chatbot pada aplikasi. Platform e-commerce yang terlibat dalam penelitian ini adalah lima e-commerce terbesar yang digunakan di Indonesia yaitu Shopee, Tokopedia, BliBli, Lazada, dan Bukalapak. Data yang terkumpul dianalisis menggunakan metode partial least squares structural equation modeling. Hasil penelitian menunjukkan bahwa keterampilan percakapan chatbots dapat mempengaruhi keputusan belanja konsumen yang dapat meningkatkan penjualan organisasi e-commerce. Hasil penelitian ini dapat memberikan panduan untuk e-commerce dalam menggunakan chatbots untuk membantu konsumen berbelanja.

Kata kunci— *Conversational Skills; Chatbot; E-Commerce; Indonesia; Purchase Behavior*

I. INTRODUCTION

Today, the rapid development of e-commerce requires companies using it to further improve their customer service. As a result, customer service has had to adjust to new technological developments. At first, customer service still relied on call centers staffed by many people involved with the company. Now, customer service is shifting to maximize social media and other technologies in various ways, including the use of live chat, chatbots, email, the WhatsApp and Line apps, and online call centers. Prior to the use of chatbots, companies had several complaints regarding human-based customer service, including it not being available 24 hours, customers repeating many standard questions once connected to a human agent, high numbers of call center interactions every day, and customer service requiring a high budget (Morgan, 2016). Today's customers have become more comfortable with self-service options to solve their own problems. Thus, a computer chat bot or chatbot is a

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practical solution and can be a long-term customer service investment, which will replace more call center-based solutions over time. A survey by Microsoft (2017) reported that 63% of millennials are starting to interact with customer service online. As these younger demographic ages, they will likely continue this behavior, meaning it will be good to invest in online customer service for this generation and those that follow it.

E-commerce companies that have grown rapidly globally must always maintain good customer service contacts. As a country with a large population, Indonesia has a large number of e-commerce users, which is increasing. For example, the number of Shopee visitors from Indonesia has reached 55.9 million (Sirclo, 2020). Tokopedia also shows similar numbers, with the number of Indonesian visitors to its site reaching 84.9 million (Sirclo, 2020). In consideration of these numbers and the advantages possessed by chatbots, the development of this feature for customer satisfaction and as an investment is important for e-commerce in Indonesia.

Studies have been carried out to help improve chatbot implementation and analyze chatbot usage intentions for mobile shopping applications, social media, and small and medium-sized enterprises (SMEs). Few studies have discussed chatbots' direct influence on e-commerce. Schuetzler et al. (2020) focused on whether chatbot skills were able to increase partner engagement and the perceptions of users who attributed human feelings to chatbots. Toader, et al. (2020) showed that respondents were more willing to buy a product after interacting with a chatbot that made no errors in responding to the customers. Selamat and Windasari (2021) analyzed the features and elements that fit with SME characteristics and their customers' fit with chatbots. Huang and Chueh (2021) developed a chatbot prototype for veterinary consultations. Kasilingam (2020) evaluated the intention of consumers to use chatbots on smartphones for shopping. Moreover, Stieglitz, et al. (2018) proposed a research model for using enterprise bots. Araújo and Casais (2020) and Rese, et al. (2020) analyzed user acceptance of chatbots with online retailers. Illescas-Manzano, et al. (2021) implemented a chatbot as a digital marketing strategy via Facebook Messenger for a company's sales funnel. Moreover, Smutny and Schreiberova (2020) examined educational chatbots for Facebook Messenger to support learning.

Schuetzler et al. (2020) stated that there is a scarcity of research that has examined behavioral aspects of human–chatbot interactions. In this study, we focus on the behavioral aspects in terms of purchasing behaviors and attitudes expressed by individuals who have recently had chatbot interactions. This is because the human factors of chatbots can affect consumers directly and make customers feel satisfied with the use of these features (Schuetzler et al., 2020). Moreover, chatbots are systems that act in more humanlike ways, so conversational skills become the main function that can influence the interactions between humans and chatbots (Schuetzler et al., 2020). The current study was conducted to confirm and add to the previous research developed by Schuetzler et al. (2020), Toader et al. (2020), and Selamat and Windasari (2021) by the addition of variables, namely trust, customer satisfaction, purchase intention, and actual purchase behavior. The addition of these variables was to achieve the aim of this study: to examine the effect of conversational skills on chatbots on real purchases in e-commerce. Thus, the results of this study can enrich the literature by analyzing the influence of chatbot conversation skills on the actual purchase behavior of e-commerce users in Indonesia. Finally, this study can provide guidance for e-commerce platforms in the effective use of chatbots for customer service.

II. LITERATURE REVIEW

A. *Chatbot*

The first-level subsection heading should be in 12-point bold with the first letter of each word capitalized. A chatbot is a software agent that interacts with users using natural language (Følstad & Brandtzæg, 2017). Thus, chatbots are a promising technology for customer service applications. For online service providers, the quality of service offered through chatbots is very important for strengthening service relationships with customers (Følstad & Brandtzæg, 2017). Chatbots, also referred to as agents, can provide access to data and services naturally through language interactions. Although the term "chatbot" is relatively new, computer systems that interact with users in natural language have been developed and researched since the 1960s (Følstad & Brandtzæg, 2017).

Currently, several technology companies provide platforms that can support chatbots for customer service, including IBM's Watson, the Microsoft Bot Framework, and Google's DialogFlow (Nuruzzaman & Hussain, 2018). Zaboj (2020) showed that customers do not mind being served by a chatbot if it can solve their problems quickly. Moreover, a chatbot can utilize its question-and-answer interface to ensure that the most frequently asked questions are displayed at the beginning. Chatbots have several advantages, namely the ability to answer repetitive questions, the ability to serve millions of customers at once, integration with various channels or an omnichannel, and availability 24 hours a day without an administrator present.

There are two types of chat that are usually provided in e-commerce: rule-based chatbots and artificial intelligence (AI) chatbots (Sadekov, 2020). A chatbot can provide a frequently asked questions (FAQ) document, questions with direct answers, or a live chat (Sadekov, 2020). This research focuses more on chatbots within the scope of FAQ providers and live chat. The selection was based on the types of chatbots that have been implemented in e-commerce in Indonesia. Another type is called a live agent. A live agent has several advantages, including being able to address complex questions, finding customer "pain points" faster, replying to messages according to customer sentiment, and multitasking. These advanced features require more advanced processing, which generally means the application of AI techniques.

B. Conversation Skills

Conversational skills are employed by a chatbot, and natural language processing (NLP) is used by the computer system to assist in interactions with humans (Schuetzler et al., 2020). The main concept behind chatbots is that they need to possess the skills to provide users with meaningful interactions (e.g., by providing them with information they desire or need). In making a chatbot, the most important consideration is the quality of the conversations in which it can engage (Chaves & Gerosa, 2018). A chatbot must adopt features and characteristics that provide a high-quality conversation experience tailored to the language of the user (Chaves & Gerosa, 2018).

By implementing human–computer interactions that are convenient for a user, a chatbot or virtual assistant will be judged favorably and will be accepted by users (Chaves & Gerosa, 2018). With the context described above and knowing the importance of a chatbot's skills in managing the language, several efforts have been undertaken by chatbot developers. Many of the companies developing these chatbots are already to move on to the next step and are looking for conversational copywriters, who are often called conversation designers (Han, 2021). One example is Label from Robocopy, which is currently working with large companies and has data that conversational copywriting is the next step in the bot revolution (Han, 2021). However, having a copywriter does not signify a completely successful project because right now it is not about how well the software understands the language; it is about how well the user understands what the software is trying to achieve and how well the bot company designs the conversations that make this happen. Table 1 presents demonstrative examples of different chatbots' response tailoring and variety based on Schuetzler et al. (2020).

Table 1.Examples of chatbots' response tailoring and variety (Schuetzler et al., 2020).

Initial Interaction	Generic Non-varied Response	Generic Varied Response	Tailored Non-varied Response	Tailored Varied Response
Chatbot: What did you do on your last birthday? User: My friends and I went hiking.	Chatbot: That's nice.	Chatbot: That sounds like fun.	Chatbot: I also enjoy hiking.	Chatbot: Nice, hiking is really fun!
Chatbot: What did you do last Friday? User: I played video games.	Chatbot: That's nice.	Chatbot: Cool!	Chatbot: I also enjoy playing video games.	Chatbot: Cool, are you good at playing video games?

C. Social Presence Theory

Social presence theory (SPT) refers to the number and quality of verbal and nonverbal channels in a communication medium (Schuetzler et al., 2020). Toader et al. (2020) also showed that the perception of social presence is important in developing strong trust beliefs; in this way, more evidence has been provided that social presence and perceived competence are indeed the most important determinants of trust in an interaction. Furthermore, according to Bickle et al. (2019), social presence is the degree to which a person is perceived to be a "real person" in a computer-mediated communication or virtual environment. This theory also states that the ability of a medium to facilitate feelings of social connection, regardless of a person's direct presence, varies depending on the communication medium, in this case, through chatbot media (Schuetzler et al., 2020).

D. Actual Purchase Behavior

Actual purchase behavior describes the extent to which a customer decides to make a purchase in the context of online shopping. According to Tsai et al. (2019), actual purchase refers to the process of searching, selecting, buying, using, and evaluating a product or service to satisfy the needs and desires of a customer. The decision-making process can reflect the level of consumer desire to pay for a product or service of interest (Tsai et al., 2019). The output of purchase decisions reflects the final choices of a consumer. Peter and Olson (2010) said that actual purchase decisions are an important part of the process leading to an action taken by customers because customers tend not to buy products with high-risk perceptions. Sellers try to manage customer perceptions about the consequences of buying and using a product and enrich customer knowledge about a product.

E. Conceptual Model

For this study, variables were identified through a selection process and adapted to the specific setting and problems that exist in Indonesia regarding this topic. In addition, the indicators used in this study were variables that were in accordance with the context of the application of chatbots that influence customer decisions in making purchases in e-commerce. We adopted four variables from Schuetzler et al. (2020): tailored response, response variety, social presence, and perceived humanness. These variables used by Schuetzler et al. (2020) were chosen as they related to the research topic of analyzing chatbot conversation skills. Furthermore, we adopted the trust variable from Yen and Chiang (2021). In the current study, trust was related to the user's trust of sellers and chatbots. The context of the research conducted by Yen and Chiang (2021) was similar to ours. Furthermore, we adopted the purchase intent variable from Han (2021) in consideration of its attachment to social presence. The last three variables, namely customer satisfaction, purchase intention, and actual purchase behavior, were adopted from Toader et al. (2020). The current study included two exogenous variables and one endogenous variable. This research model has eight variables, nine hypotheses, and 38 measurement items (Figure 1).

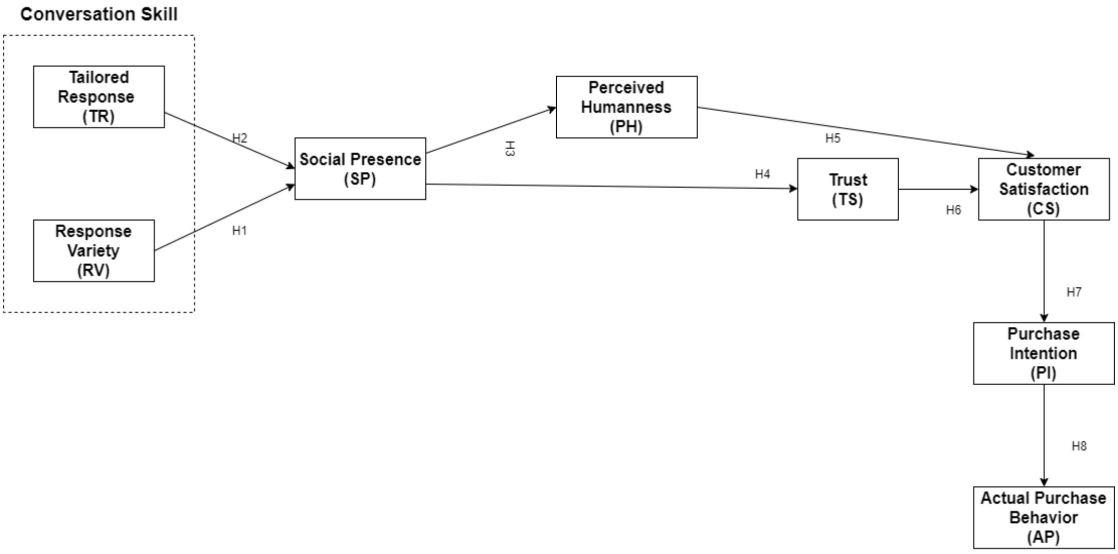

Fig. 1.Proposed conceptual model.

A tailored response is defined as a chatbot message sent directly as the result of a message received from a user and according to its context (Schuetzler et al., 2020). Hence, chatbots must have language skills that are adapted to human everyday language to provide tailored responses. Social presence or virtual togetherness represents the feeling that an interlocutor lives in the same world, and this includes chatbots in terms of how they react to human questions (Schuetzler et al., 2020). It is said that a conversational agent can simulate human conversational skills by providing a tailored response in which the conversational agent adjusts its own dialogue based on what people say as part of an interaction (Schuetzler et al., 2019). The chatbot will double check the details of a user's message and assign a customized answer script (i.e., a tailored response) (Toader et al., 2020). This will create a pleasant chat experience for users who engage with the bot and is expected to provide a much higher conversion rate and customer satisfaction from the services offered (Toader et al., 2020). This relationship between tailored responses and social presence creates cues about the social capabilities of chatbot conversational agents. As such, the following hypothesis was proposed:

H1 A tailored response (TR) will have a positive influence on social presence (SP).

Response variety is defined as interactions through messages in which some variations in words and phrasing are used to convey the message, even though the meaning may be the same. Computers are programmed and, for simplicity, will basically respond by issuing the same output to a particular condition every time, and this deterministic property of computers is fundamental and is generally a positive feature (Schuetzler et al., 2020). In interactions with chatbots, when there are variations in the wording and phrasing of responses, the conversation appears more human and natural to the user. A response variety variable is needed in a chatbot context because a lack of variety will be perceived as lower conversational skills or may even be viewed as disturbing in the implementation of a chatbot (Schuetzler et al., 2019). Conversational skill factors reduce generic and repetitive responses; the researcher collected additional data in which participants were assigned to interact with bots that gave a variety of answers and had different impacts (Schuetzler et al., 2019). Feine et al. (2020) have shown that the language used by chatbots has improved according to the researcher's search for language variations (Feine et al., 2020). Social presence is defined as a perception of virtual togetherness that represents the feeling that the interlocutor lives in the same world and that chatbots do so in reacting to human questions (Schuetzler et al., 2020). Social cues exhibited by a chatbot, such as its ability to engage in human-like conversations with a variety of responses, are likely to increase the agent's social presence as perceived by the user. As such, the following hypothesis was proposed:

H2 Response variety (RV) will have a positive influence on SP.

Social presence represents the feeling that an interlocutor lives in the same world, and this can also apply to chatbots when individuals see their responses to questions (Schuetzler et al., 2020). Toader et al. (2020) found that the addition of an avatar on a retail website resulted in a feeling of social presence that led to higher attitudinal satisfaction as well as greater purchase intention. They suggested that the use of perceived humanness as a cue in an online retail context result in an increase in perceived social presence on websites. Moreover, social presence has been found to significantly influence bidding and buying behavior in e-marketplaces (Adam et al., 2020). A social cue presented by a chatbot can affect a sense of connection with individuals in ways that are similar to mediated conversations between people. Social cues shown by a conversational agent, such as its ability to engage in conversation like a human (perceived humanness), should increase the agent's social presence as perceived by the user (Schuetzler et al., 2020). Given the importance of the concept of social presence in the context of human–computer interaction, several studies have looked at the impact of virtual agent anthropomorphism on perceived social presence on websites [5]. As such, the following hypothesis was proposed:

H3 SP will have a positive influence on perceived humanness (PH).

Toader et al. (2020) stated that social presence has a relationship with trust. The social presence that is implemented in the chatbot will give the impression that the chatbot is present and always there, if needed, when the chatbot system is accessible 24 hours a day (Toader et al., 2020). In addition, Adam et al. (2020) indicated that social presence mediates the effect of anthropomorphic design cues on user compliance, which can have a positive impact on user trust. As such, the following hypothesis was proposed:

H4 SP will have a positive influence on trust (TS).

Perceived humanness reflects how much a chatbot can achieve high human-like characteristics within a system (Schuetzler et al., 2020). Perceived humanness will have a much higher influence if the involvement of the customer with the chatbot provides relevant answers that are comparable to asking other people (Schuetzler et al., 2020). Go et al. (2019) indicate that the efforts made by chatbot chat agents with AI are sufficient to make them seem more human-like. One proposed way to increase the humanity of chat agents is by using the concept of an anthropomorphic human figure, which is a cue from an agent that shapes social perception (Go et al., 2019). Svenningsson and Faraon (2019) showed that a chatbot must have the characteristics of avoiding small talk and maintaining a formal tone, being able to identify that it is a bot that can help customers and providing specific information with sophisticated word selection with sentences that are well structured. Schuetzler et al. (2020) have shown that perceived humanness influences customer satisfaction. Systems are made to act as human as much as possible so that people respond by adopting conversational norms and raising expectations of the system's capabilities (Schuetzler et al., 2020). Ultimately, this can lead to increased satisfaction and perceived benefits (Svenningsson & Faraon, 2019). Perceived humanness that is implemented in the chatbot system cannot completely replace the human role in making decisions or answering questions. However, if a chatbot implements a higher perceived humanness, it will make customers feel comfortable and will increase satisfaction in using the feature. As such, the following hypothesis was proposed:

H5 Perceived humanness (PH) will have a positive influence on customer satisfaction (CS).

Nordheim et al. (2019) state that trust in chatbots can arise from the chatbot's ability to interact naturally with language. According to Yen and Chiang (2021), trust is defined as a person's attitude of reliability or confidence in something or someone, which will be fundamental to building and maintaining relationships. The tendency for someone to trust technology begins if a person and the chatbot are in contact via an interactive system, and the system is always available when needed (Yen & Chiang, 2021). Chatbots can help a business to improve the customer experience and meet customer's expectations in receiving direct replies as a result of interactions in e-commerce (Yen & Chiang, 2021). Customer trust is very important, so new online technologies designed to be human-like are likely to be adopted in the market. Especially with natural language interactions, trust can be a very important component of these systems (Nordheim et al., 2019). The expertise possessed by chatbots can be felt and has the possibility of having a positive effect on customer satisfaction (Nordheim et al., 2019). Nordheim et al. (2019) stated that some customers expressed satisfaction in using chatbots because they did not provide sensitive answers. Yen and Chiang (2021) claimed that trust is an important predictor of the success of a machine or technology. However, they also said that some customers cannot fully trust that chatbots will provide the same level of service as human representatives. In chatbots designed with trust in mind, answers that are honest and fast can be provided with a minimum of incorrect answers. If this can be achieved, it will create an impression of trust for customers. Furthermore, customers will be satisfied with the services provided. As such, the following hypothesis was proposed:

H6 TS will have a positive influence on customer satisfaction (CS).

Customer satisfaction is an assessment and opinion felt or expressed by customers (Biesok & Wyrod-Wrobel, 2017). The level of customer satisfaction can be said to be the gap between the customer's goals and their perception of a product or service (Biesok & Wyrod-Wrobel, 2017). If the interaction of a service agent and customer meets the customer's expectations, it will affect customer satisfaction, loyalty, positive word-of-mouth, and purchase intentions, which will result in profits for the company (Chung et al., 2020). In the past, interaction was carried out directly face-to-face; since the creation of social networks, online interactions fulfill customers' needs for a fast response outside of the actual facility (Chung et al., 2020). Ali (2016) obtained results on how e-service agents can affect the quality of communication and customer satisfaction; service providers in each industry are trying to provide a customer satisfaction component because it has an impact on their profits. Customer satisfaction is influenced by a chatbot because it can create the impression that there is no gap between the customer and the company (Deloitte, 2019). There are several ways to make customers satisfied, including through their use experience, being proactive, providing product references in e-commerce, and relating to the user's personal experience in the context of a conversation. If these attempts are deemed sufficient, it will create a sense of satisfaction for customers, who will be more like have intentions to buy products on e-commerce. In the application of a chatbot feature in e-commerce, if the customer is satisfied with its use, the interaction will lead to a high intent to purchase. As such, the following hypothesis was proposed:

H7 CS will have a positive influence on purchase intention (PI).

Purchase intention is an important variable to measure regarding potential actions that consumers choose to take (Agmeka et al., 2019). Purchase intention can help companies understand the market and adjust the offering of products or services so that they can improve sales and earn profit (Agmeka et al., 2019). Moreover, purchase intention is defined as the buyer's desire to engage in exchange interactions on shopping sites, such as sharing information, maintaining business relationships, and creating business transactions (Dachyar & Banjarnahor, 2017). Purchase intention is a factor that can predict actual purchase behavior or purchase decisions by customers (Agmeka et al., 2019; Dachyar & Banjarnahor, 2017). As such, the following hypothesis was proposed:

H8 PI will have a positive influence on actual purchase (AP).

III. RESEARCH METHODOLOGY

A. Research Instrument

This study has been approved by Faculty of Computer Science Universitas Indonesia. This study used an online questionnaire for data collection (quantitative approach). The respondents involved in this study were e-commerce users who had shopped on an e-commerce platform and had used the chatbot feature on the platform. The e-commerce platforms referred to are Shopee, Tokopedia, BliBli, Lazada, and Bukalapak. Before the questionnaires were distributed to the respondents, the authors conducted a readability test to examine the questionnaires. The questionnaire was written in the Indonesian language.

In the validation question part, we asked the respondent a validation question, namely "Have you ever used a chatbot at least once provided by e-commerce and shopped at least once through several e-commerce applications?" If the respondent answered no, the respondent could not fill out the questionnaire and if the respondent answered otherwise the respondent could fill out the questionnaire. The questionnaire used in this study consisted of three parts. The first part contained questions asked to obtain information about the demographics of the respondents. The second part contained questions related to chatbot features in the e-commerce application, and the third part contained questions related to testing the proposed model. Each question was designed to use a Likert scale ranging from one to five, consisting of strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5). Appendix A describes the research instrument.

The readability test of the questionnaire examined it in terms of the rules of writing and the meaning of the statements so that the respondents could clearly understand the meaning of the statements provided. The readability test was carried out over one week, from February 2, 2021, to March 1, 2021, by gathering six people from different backgrounds. The respondents who participated in the readability test met the general criteria for the research sample, namely, having shopped online and used a chatbot at least once in e-commerce in Indonesia. The results and feedback from the readability test were used to improve the text (such as grammar) of the questionnaire.

B. Data Collection

Data collection was carried out online, not only due to the limitations caused by the COVID-19 pandemic but also so that it could reach respondents from various regions in Indonesia and would be easily accessible by respondents anywhere and anytime. The questionnaire link was shared through social media platforms that were widely used by Indonesian people, such as Facebook and Instagram. Each respondent who was involved in this study provided informed consent regarding their participation in the study. The data collection was carried out for a period of approximately one month, from March 2 to April 1, 2021.

C. Analysis Methods

The statistical data processing was carried out using partial least squares-structural equation modeling (PLS-SEM). We used PLS-SEM due to this study was exploratory research and has the aim of testing the relationship between the constructs by seeing whether there is a relationship or influence between the constructs. The software packages that the researcher used to perform the data processing were AMOS 24.0, SPSS 25, SmartPLS 3.3.2, and Microsoft Excel. SmartPLS 3.3.2 was used to perform the PLS-SEM analysis; IBM SPSS AMOS 24 was used to identify and eliminate outliers; IBM SPSS Statistics 25 was used to test common method bias; and Microsoft Excel was used to assist in processing and organizing data from the survey results and test results.

The stages used in the PLS-SEM analysis will include model specification, outer model (measurement) evaluation, and inner model (structural) evaluation (Hair, et al., 2012). The measurement model test using PLS-SEM aims to be able to see the validity and reliability of the construct size in the existing outer model (Hair et al., 2012). In the measurement model evaluation, several processes are carried out, namely the evaluation of composite reliability (CR) and average variance extracted (AVE). At this stage, the outer model evaluation using PLS - SEM aims to facilitate testing of the quality of the model (Hair et al., 2012). The method taken is to evaluate the path coefficient, coefficient of determination (R2), cross-validated redundancy (Q2), and effect size (F2) (Hair et al., 2012).

IV. RESULT/FINDING

A. Respondent Demographics

The total data that were successfully obtained were from 699 respondents. However, in data processing, there were duplicate data, and some questionnaires were not filled in completely so that the total number of respondents who submitted usable data was 650. A summary of the respondents' demographic information can be seen in Table 2.

Table 2. Respondents' demographics.

Demographics		Number	Percentage
Gender	Men	282	40.34%
	Women	417	59.65%
Age	17–25 years old	612	87.55%
	26–35 years old	44	6.29%
	36–45 years old	29	4.14%
	>45 years old	14	2.00%
Domicile	Greater Jakarta	498	71.24%
	Greater Jakarta in Java Island	122	17.45%
	Maluku	1	0.14%
	Bali and Nusa Tenggara	11	1.57%
	Sumatera	32	4.57%
	Kalimantan	10	1.43%
	Sulawesi	20	2.86%
	Papua	1	0.14%
	Others	4	0.57%
If you have ever shopped using a chatbot in an e-commerce, were you satisfied communicating with the chatbot?	Satisfied	391	55.93%
	Less satisfied	275	39.34%
	Not satisfied	33	4.72%
On which e-commerce app do you shop by interacting with a chatbot? (Can choose more than one)	Blibli	18	2.57%
	Shopee	568	81.25%
	Lazada	86	12.30%
	Tokopedia	288	41.2%
	Bukalapak	41	5.86%
	Lainnya	26	3.71%

B. Measurement Model

The measurement model test (outer model) was the next stage after forming the path diagram. This was carried out to ensure that the indicators represented the construct so that further structural model testing could be carried out (Hair et al., 2012). The factor loading values met the requirements suggested by Hair et al. (2012), with the value for each variable above 0.7. Moreover, a convergent validity test was viewed from the AVE values and loading factors, and then the discriminant validity test was viewed in terms of the AVE square root (Fornell-Larcker criterion) and cross-loading values. CR was used to measure the overall scale reliability (Hair et al., 2012). CR is often suggested as an alternative option to Cronbach's alpha. The CR test must pass the prerequisite values of more than 0.7 (Hair et al., 2012). Table 3 shows that the model in this study has met the requirements of having AVE values >0.5 and CR values >0.7. This model also passed the discriminant validity test (Appendix B).

Table 3. AVE and CR Values

Variable	AVE	CR
AP	0.817	0.964
CS	0.824	0.959
PH	0.741	0.896
PI	0.770	0.930
RV	0.710	0.830
SP	0.723	0.929
TR	0.696	0.820
TS	0.686	0.929

* Note: AP = actual purchase behavior, CS = customer satisfaction, PH = perceived humanness, PI = purchase intention; RV= response variety, SP = social presence, TR = tailored response, and TS = trust

C. *Structural Model*

This model also demonstrated that all the paths were evaluated with p-values less than 0.10 so that it can be concluded that all the paths in this model were significant, and the coefficients indicated positive relationships. The R2 values from this model show that the AP construct was strong, with a value of 6.78%; CS was strong, with a value of 6.49%; and PH was strong, with a value of 6.58%. PI was moderate, with a value of 4.15%; SP was moderate, with a value of 5.05%; and TS was moderate, with a value of 5.41%.

D. *Hypothesis Testing*

This study used a one-tailed test method where a hypothesis can be accepted if the p-value is less than the significance level, and the value of the t-statistic is greater than the minimum t-statistic value. The hypothesis test was accepted if the p-value was less than or equal to 0.05 (equivalent to the 95% significance level), while the t-statistic value must be greater than 1.65. In this study, a total of eight hypotheses were tested, and it was concluded that all hypotheses were accepted (Table 4).

Table 4. Hypothesis testing results.

Hypothesis		Path Coefficient	T Statistic	*P*-Value	Result
H1	TR → SP	0.488	12.773	5.6×10^{-14}	Accepted
H2	RV → SP	0.297	7.275	3.9×10^{-13}	Accepted
H3	SP → PH	0.811	48.441	5.6×10^{-14}	Accepted
H4	SP → TS	0.736	32.932	5.6×10^{-14}	Accepted
H5	PH → CS	0.241	5.649	1.7×10^{-8}	Accepted
H6	TS → CS	0.607	14.044	5.6×10^{-14}	Accepted
H7	CS → PI	0.644	23.811	5.6×10^{-14}	Accepted
H8	PI → AP	0.823	53.753	5.6×10^{-14}	Accepted

V. DISCUSSION

Schuetzler et al. (2020) found that tailored response variables can make someone feel that chatbots have high levels of skill in answering questions by repeating answers from customers first and then asking the next question. This study showed that there was a significant influence between the tailored response variable and the social presence variable (H1). These results are in accordance with Schuetzler et al. (2020) and SPT. About 291 respondents, or 44.76% of the total, answered that the chatbot responded with relevant responses. Therefore, tailored response was shown to be a variable that influences social presence.

Moreover, Schuetzler et al. (2020) found that it was necessary to group keywords and responses into concepts. Concepts were used to arrange words and phrases around the same word so that the chatbot could respond appropriately. For example, the greetings “hello,” “hello,” or “hey” are different phrases or forms that have the same purpose (Schuetzler et al., 2019). Schuetzler et al. (2019) collected data in which participants were assigned to interact with bots that gave varied answers with different impacts on the results. This study found that there was a significant effect between response variety and social presence (accepted H2). The results of our observations were on several e-commerce sites in Indonesia, which still had not implemented a response variety component in their chat windows, so they were still rigid and had unvarying answers. Ideally, a chatbot should be able to present understandable, varied, and not rigid responses. This was also reinforced by the answers from 314 respondents, or 48.3% of the total who answered that the answers provided by the chatbots were very rigid.

Furthermore, social presence is a valuable construct because chatbot developers try to make direct connections with users (Schuetzler et al., 2020). This study showed that there was a significant influence between social presence and perceived humanness (H3). When a user forms an impression of a social presence with a chatbot, that feeling can extend to an emotional connection with the organization or company that the chatbot represents. An emotional connection can increase people’s perceptions of the integrity and goodness of a company. For example, social presence has been found to significantly influence both offering behavior and market outcomes, as well as buying behavior in an electronic marketplace in the context of e-commerce (Adam et al., 2020). Moreover, in the current study, 174 respondents, or 26.7% of the total, recommended a feature with voice responses from the chatbots to build an emotional connection.

According to Toader et al. (2020), trust was very important in online interactions because it affected the willingness of customers to accept information and suggestions provided by chatbots. In addition, this study also showed that there was a significant influence between social presence and trust (H4). The influence of social presence on trust can be seen in the phenomenon that chatbots are used as the cheapest and fastest way to connect the company with customers and maintain those relationships. A proactively designed chatbot will create trust in e-commerce. One example is Shopee, which always proactively asks, “Do you need any more help?” This consistently reinforces the nature of trust in its customers. This study also had 568 respondents, or 87.3% of the total, who interacted with chatbots on Shopee.

In addition, this study showed that there was a significant influence between perceived humanness and customer satisfaction (H5). These results support the results of Svenningsson and Faraon (2019). To design a chatbot with a good user experience and in accordance with its objectives, the three components that will have an impact are usefulness, usability, and customer satisfaction (Svenningsson and Faraon, 2019). For example, implementing a live chat feature will improve the perceived humanness of a chatbot to users. This study describes 474 respondents, or 72.9% of the total, suggesting that e-commerce should have a live chat feature.

In customer–seller interactions, it is very important to increase customer trust by showing empathy and listening to customer concerns (Chung et al., 2020). Customers trust the reliability and completeness of accurate communications (Chung et al., 2020). According to Chung et al. (2020), few customers trust chatbots at different levels and it was found that some consumers who frequently use chatbots do not fully trust the services provided by them. This study also showed that there was a significant influence between trust and customer satisfaction (H6). Based on our questionnaire data, customers who believed in the services provided by the chatbots were around 49% of the total. Thus, it can be concluded that there is a need for improvement in building trust in existing chatbots accepted by the public. Therefore, customers’ trust in chatbots is important in understanding buying behavior in e-commerce in society (Yen & Chiang, 2021).

Weisberg et al. (2011) stated that purchase intention is influenced by service quality, customer satisfaction, loyalty, cost, and product preferences. It is argued that such judgments elicit emotions and build rapport, which, in turn, affects services, such as customer satisfaction and behavioral outcomes (Sands et al., 2021). This study also shows that there was a significant influence between customer satisfaction and purchase intention (H7). By making modifications to a chatbot, such as improving the personal customer experience, you can give personal preferences to customers. For example, in providing product references upon being asked, the chatbot can examine user behavior to interact with customers. This can then increase a customer's intention to buy a product. In this study, 60.15%, or about 391 customers, were satisfied with the services provided by chatbots on e-commerce.

In the end, this study showed that there was a significant influence between purchase intention and actual purchase behavior (H8). Han (2021) mentions that young consumers fully accept chatbot technology in their daily lives. Around 60% of millennials have used chatbots, and 70% said they had a positive experience interacting with chatbots (Han, 2021). Based on questionnaire data, 209 people, or about 32.15%, agreed on average that customers will buy goods if they interact directly with a chatbot. The evolution of technology has changed the consumer decision-making process because consumers fulfill their needs and desires with the support of digital technology (Todor, 2016). Intentions for customers to make real purchases on e-commerce can be seen from the interactions carried out with chatbots using personal preferences, which end up adding items to a customer's shopping cart. Furthermore, customers will make real purchases with the help of a chatbot.

This was a preliminary study that examined the influence of conversational skills in chatbots on consumer purchasing decisions in e-commerce. This research also contributes to trust, which is one of the factors that affects the level of chatbot usage. This study is different from that of Schutzler et al. (2020), as their study only focused on how conversational skills or chatbot skills could affect social presence. Moreover, this study is expected to provide benefits to e-commerce chatbot service providers in Indonesia. This study is also expected to provide encouragement for companies in the e-commerce field to continue to develop social presence and perceived humanness in chatbots in various ways. This study shows that the development of conversational skills in chatbots is an essential customer service feature that allows chatbots to provide quick answers compared to calling customer service directly. In addition, one of the customer expectations that was noted, which was quite unique, was to add a sign language feature. Some groups, such as deaf customers, can use a chatbot to obtain the same services as other customers. Furthermore, e-commerce organizations are expected to be able to provide impetus for chatbot development, which in this study stated that there are still obstacles in using the chatbot feature where respondents are confused by the language used by chatbots and bored with words that look stiff. Then, the respondents' expectations are chatbots being able to get answers quickly compared to calling customer service directly.

VI. CONCLUSION AND RECOMMENDATION

This study contributes to e-commerce organization that want to improve their customer service by implementing chatbot. This study shows that the conversational skills of chatbots can be used by e-commerce to influence social presence. Social presence also has a positive effect on perceived humanness and trust. Perceived humanness and trust have a positive effect on customer satisfaction, and customer satisfaction has a positive effect on purchase intention. In the end, purchase intention has a positive effect on actual purchase behavior. This study has limitations, as the respondents involved in this study were mostly respondents who were in Greater Jakarta and in the age range of 17 to 25 years. Because the social presence variable has only a moderate R2 value, other conversational skill variables can be investigated to attempt to increase the R2 value. Finally, future research could analyze the effect of chatbots on specific types of e-commerce, such as mobile commerce.

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Appendix A. Research Instruments

Code	Statement
TR1	The chatbot will always respond with the exact same response to the question asking for more detail.
TR2	Chatbots use natural language to provide responses that are relevant to messages.
TR3	Chatbots respond differently to repeated questions.
TR4	The response I receive from the chatbot increases my sense of openness to chatbots.
RV1	The chatbot provides the same response every time (e.g., each time you agree to a statement, it always responds “Yes”).
RV2	The chatbot provides a variety of responses to follow-up questions (e.g., it has a variety of follow-up responses, such as “Is there anything else I can help with?” and “Are there any more problems?”).
RV3	I feel that chatbots use natural language in their processing and provide message-relevant responses.
RV4	I feel like the chatbot doesn’t change its responses in any way, but instead returns the same response to every picture and message from me.
SP1	I feel that it is similar to human contact when interacting with the chatbot.
SP2	I feel a sense of human warmth even though I don’t see the chatbot agent.
SP3	I feel a sense of friendliness when interacting with the chatbot.
SP4	I feel there are people who can be a source of comfort for me when using a chatbot.
SP5	I feel like there’s always someone I can ask when I need direction in using a chatbot.
PH1	I feel that chatbots are human-like.
PH2	I feel that the chatbot provides a realistic response.
PH3	I feel that the chatbot is always present (can be contacted at any time).
PH4	I feel that the chatbot is genuine.
TS1	I feel the chatbot can be trusted.
TS2	I think this chatbot will be profitable for me.
TS3	I’m confident with the chatbot.
TS4	I feel the chatbot seems sincere while interacting with me.
TS5	I’m sure the chatbot provides honest responses when interacting with me.
TS6	I believe that chatbots provide credible answers during their interactions with me.
CS1	I am satisfied with the chatbot service.
CS2	I feel the chatbot is doing a great job.
CS3	I feel like the chatbot is doing what I expect.
CS4	I am happy with the chatbot service.
CS5	I am satisfied with the experience of interacting with the chatbot.
PI1	If I’m going to buy a product, I'll consider interacting with the chatbot.
PI2	My chances of shopping will be higher because of the chatbot.

Code	Statement
PI3	My willingness to buy products is high if I interact with the chatbot.
PI4	I will consider buying the product after interacting with the chatbot.
AP1	I often buy e-commerce products because of the satisfying chatbot service.
AP2	I intend to continue buying products on e-commerce applications with the help of chatbots.
AP3	I often buy products by getting information from the chatbot because it is very easy to do.
AP4	I often buy products with the help of a chatbot because it is more convenient.
AP5	I often buy products with the help of a chatbot for my needs.
AP6	I often buy products with the help of a chatbot because it safe to use.

Appendix B. Cross-loading Values

	AP	CS	PH	PI	RV	SP	TR	TS
AP1	0.875	0.555	0.563	0.772	0.367	0.601	0.480	0.578
AP2	0.880	0.560	0.574	0.761	0.380	0.609	0.463	0.586
AP3	0.917	0.600	0.528	0.735	0.356	0.586	0.448	0.586
AP4	0.932	0.598	0.552	0.753	0.392	0.625	0.464	0.593
AP5	0.918	0.578	0.546	0.726	0.369	0.581	0.445	0.575
AP6	0.901	0.579	0.542	0.712	0.379	0.586	0.443	0.595
CS1	0.544	0.893	0.623	0.571	0.450	0.624	0.579	0.700
CS2	0.518	0.884	0.590	0.517	0.458	0.584	0.578	0.705
CS3	0.607	0.913	0.635	0.601	0.453	0.651	0.571	0.722
CS4	0.609	0.921	0.667	0.606	0.486	0.652	0.598	0.725
CS5	0.621	0.929	0.670	0.623	0.464	0.677	0.591	0.735
PH1	0.551	0.609	0.886	0.558	0.457	0.773	0.556	0.618
PH2	0.514	0.644	0.871	0.507	0.471	0.684	0.565	0.674
PH4	0.511	0.559	0.825	0.516	0.369	0.631	0.479	0.679
PI1	0.628	0.598	0.523	0.823	0.397	0.549	0.511	0.529
PI2	0.763	0.562	0.539	0.912	0.382	0.594	0.478	0.567
PI3	0.770	0.562	0.564	0.920	0.369	0.603	0.483	0.584
PI4	0.722	0.541	0.522	0.851	0.358	0.577	0.462	0.573

	AP	CS	PH	PI	RV	SP	TR	TS
RV2	0.332	0.422	0.351	0.314	0.793	0.425	0.407	0.382
RV3	0.366	0.440	0.485	0.401	0.890	0.568	0.607	0.456
SP1	0.552	0.618	0.724	0.571	0.522	0.873	0.611	0.616
SP2	0.585	0.597	0.713	0.580	0.503	0.895	0.567	0.610
SP3	0.475	0.563	0.593	0.485	0.553	0.807	0.549	0.600
SP4	0.642	0.595	0.714	0.629	0.474	0.872	0.564	0.645
SP5	0.553	0.613	0.695	0.544	0.489	0.799	0.558	0.652
TR2	0.278	0.485	0.424	0.320	0.568	0.443	0.765	0.473
TR4	0.530	0.581	0.593	0.563	0.485	0.650	0.898	0.559
TS1	0.539	0.658	0.694	0.529	0.390	0.624	0.479	0.840
TS2	0.550	0.668	0.625	0.579	0.412	0.609	0.559	0.832
TS3	0.599	0.707	0.668	0.609	0.402	0.643	0.535	0.883
TS4	0.571	0.605	0.661	0.537	0.474	0.683	0.530	0.789
TS5	0.458	0.632	0.572	0.450	0.403	0.554	0.492	0.837
TS6	0.491	0.653	0.545	0.473	0.404	0.530	0.489	0.782