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Consumer behavior switching from human agents to chatbots in the health service industry

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ABSTRACT

Artificial intelligence (AI) technology is used in organizations to replace human services with technology, altering customer service experiences. Only a limited number of studies have explored how consumers change their behavior from human-assisted to technology-assisted services when using AI in frontline and specialty healthcare services. This study examined the elements that impact consumers' transition from human agents to AI-based conversational agents using the push-pull mooring framework. Data from 147 healthcare users was evaluated using structural equation modeling. The data indicates that push effects, specifically adaptability, have a negative impact on switching behavior, while pull effects, such as responsiveness and accessibility, have a positive impact on the switching behavior of customers.

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1. INTRODUCTION

The world is currently experiencing significant digital transformation and undergoing notable shifts. There is a growing population of online consumers, and the business environment is evolving rapidly. As a result, companies are striving to differentiate themselves in e-retailing by offering exceptional customer service and enhancing the overall customer experience and customer journey. These changes are implemented to stay competitive and redefine the role of chatbots in their business operations. Over the past years, chatbots have become a seamless part of the online experience, making it difficult for users to determine if they are speaking with a chatbot or a real person. Therefore, chatbots are considered as a potential customer service solution. The rapid advancement of artificial intelligence (AI) has transformed the way companies engage with customers, providing them with new avenues to interact through chatbots and revolutionizing the overall customer experience. In 2021, AI technology revolutionized contact center services by assuming the forefront of customer support across many sectors. By 2026, the worldwide chatbot market will reach $10.08 million [1].

AI chatbots are currently being utilized in multiple industries, including the hospitality industry, food and beverage industry, and showbiz industry. The impact of AI technology can vary across these industries. Studies have examined consumer interactions with chatbots in the health marketing communication sector, a rapidly expanding chatbot technology industry [2]. AI-based healthcare chatbots, as text-based conversational agents, have been enthusiastically embraced. Chatbots are believed to personalize and simplify access to digital healthcare services [3]. Due to the COVID-19 pandemic, businesses and organizations worldwide have introduced chatbots to offer current information on the fast-shifting circumstances [4]. The centers for disease control and prevention (CDC) utilize chatbots to handle a significant number of user inquiries daily from the United States [5], an achievement that would be impossible, or at the very least, highly challenging to attain if online support was solely managed by humans in general [6]. The COVID-19 pandemic has challenged businesses, prompting retailers to adopt chatbots as a versatile alternative, especially in Indonesian healthcare. Various healthcare facilities have adopted chatbots including hospitals, clinics, health laboratories, and health insurance providers. Skjuve *et al.* [7] state that consumer responses to communication built from humans and chatbots will differ when compared more deeply. The COVID-19 pandemic has triggered the emergence of the popularity of implementing AI in the healthcare industry. The implementation of chatbots in the healthcare industry has become an increasingly popular trend. During the COVID-19 pandemic, numerous chatbot applications were developed to meet the public's need for healthcare services and reliable information about COVID-19. Various organizations and governments have launched health chatbots as a reliable source of accurate data [8]. Chatbots are used to help patients and visitors of healthcare facilities obtain the information they need quickly and efficiently like patient registration or answer common questions. Several healthcare facilities in Indonesia have implemented chatbots in their current services. Some examples include Premier Hospital with the name RSDHealth, Prodia with the name Tania, Siloam Hospital with the name Silvia, BPJS Kesehatan with the name Chika, RS Mitra Keluarga with Mika, and others.

In many industries, the adoption of chatbots provides a level of convenience and proactive assistance that surpasses the capabilities of customer service personnel. Therefore, many industry players are currently transitioning from using human representatives to utilizing chatbots [9]. In the healthcare industry, the presence of chatbot in general have helped consumers and the public obtain various healthcare information easily and conveniently, which they can do anytime and anywhere. This ease of access has become one of the factors driving various healthcare industries to improve their service satisfaction. According to a survey conducted by Deloitte Indonesia in 2018, approximately 70.2% of respondents have never accessed digital healthcare services due to a lack of trust in digital platforms. They prefer direct communication and consultation with human service agents in healthcare services for reasons such as satisfaction with answers, legality, and privacy concerns. Ye *et al.* [10] states that many healthcare consumers are reluctant to use AI-based services due to concerns about the quality of service provided by non-human agents. Consumers have doubts about whether the services they require are appropriate, and at the same time, they expect clear and precise responses to their inquiries. Nonetheless, the information given by each agent may be inadequate and inconsistent among different human agents. Furthermore, the utilization of human agents is frequently influenced by individuals' emotional states and circumstances. Frequently, we encounter situations where agents in healthcare services offer only concise and minimal responses to our inquiries, and occasionally, human agents fail to comprehend the consumer's situation, leading to a less satisfactory response for the consumer. Another aspect of using chatbots in the healthcare industry is to assist human agents in interacting and responding to various consumer questions automatically, 24/7. The increased responsiveness of chatbot AI is expected to meet consumer expectations for service. AI chatbots can offer more responsive and faster information compared to human agents in conventional customer service channels. This possibility leads to a potential shift from traditional telephone services with human agents to conversational services supported by AI [11].

Currently, there is not much research exploring customer behavior switching from human services to technology-based services in relation to the implementation of AI in customer service in the healthcare sector. Based on the population theory Moon [12], the use of the push-pull-mooring (PPM) framework, based on the theory of population migration, is proposed. The PPM framework consists of push, pull, and mooring factors. Several studies using the PPM concept have been widely applied in various disciplines to examine the phenomenon of consumer switching behavior, whether it involves transitioning from old methods to new methods or analyzing changes in purchasing behavior between online and offline platform customers [13]. Through this, researchers want to understand what factors influence changes in consumer behavior in the healthcare service industry from using human agent customer service to AI-based services. In addition, researchers also want to know how push, pull, and mooring factors affect consumer switching behavior.

2. LITERATURE REVIEW

Chatbots are a type of computer software that can simulate human conversation, both verbally and in writing, and serve as virtual assistants for users in using services [14], [15]. The use of chatbots is currently growing rapidly in society and is used in various fields, including marketing, customer service, education, health, culture, and entertainment [16], [15]. The growing use of AI-based technology in companies has a variety of transformative impacts on the organization itself. By implementing AI technology at the front line of an organization, customer service experiences that once began with conventional service interactions are beginning to shift with the presence of service representatives who use technology [17].

The development of AI technology with the use of chatbots has not been studied much further. Currently, only a few studies have explored the shift in customer behavior from services facilitated by humans to services facilitated by technology in relation to the implementation of AI in the front-line service of an organization [17]. There is an increase in the use of AI in healthcare. In this situation, AI-based chatbots can function as automated conversational agents, offering health-related information and possibly influencing behavior change. Researching user motivation in using chatbots in the healthcare industry is necessary to see how chatbots can play a role in handling services. Only a few studies have explored the acceptance of chatbots in healthcare [18]. This study looks at how healthcare consumers behave when transitioning from human-agent contact center services to AI-based conversational agents. The researchers will utilize the PPM framework to analyze the determinants and factors that influence this behavioral switch.

2.1. Push-pull-mooring framework

The PPM framework was initially created as a theoretical perspective to determine why individuals migrate from one geographic location to another [19]. Bansal *et al.* [20] revealed that in the PPM framework, each type of factor, starting from push, pull, and mooring, represents various patterns of consumer behavior that emerge in the pattern of service switching. The PPM framework has been extensively utilized in consumer behavior change research. One implementation of its use is when the PPM framework was used in the research Li and Zhang [17], which explored the determining factors that influence the behavioral switching of consumers from using human agents to using AI-based conversation agents in the banking industry, which resulted in a positive effect on the behavioral change, both from the push effect and the pull effect. This PPM method has been applied in various industries, such as research on behavioral change in the airline industry [21], the switching behavior of mobile instant messaging applications [22], behavioral change in online learning during the COVID-19 pandemic [23], and many more. According to Hou and Shiau [24], the notable advantage of the PPM framework lies in its capacity to categorize different factors based on theoretically established classifications.

Considering these results, many studies have applied the PPM framework to investigate consumer switching behavior from one way to another. Specifically, the PPM framework provides a comprehensive model that can help researchers examine the role of push, pull, and mooring factors on the switching intention of service users in the healthcare industry. In the healthcare industry, this framework can be used to explore the factors that influence patients' decisions to adopt chatbots over traditional customer services.

2.2. Push effects: empathy and adaptability

The concept of push effects or push factors refers to negative factors that drive customers to switch from human-mediated customer service to AI-mediated customer service. Customer service generally uses humans as agents to receive various information and problems needed by customers. Interaction in customer service using humans as agents is a two-way interaction between humans that is categorized into push effects. Burgers *et al.* [25] described four main customer expectations regarding the behavior of workers in customer service, namely adaptiveness, assurance, empathy, and authority. Referring to the classification of Burgers *et al.* [25] related to the identification of customer expectations, in this study, we use two main factors, namely empathy, and adaptability, as push factors because those reasons represent two things that represent the characteristics of humans as factors that are part of human agents. The first factor is adaptability. Low adaptability of service will have an impact on customer dissatisfaction [25]. This low adaptability is defined as how human agents cannot realize customer wants and are unable to adjust their service behavior appropriately. When consumers feel that they cannot meet their needs, they may consider alternative services owned by the company, which can increase their intention to switch to AI-based service agents. The second factor that drives human agency is the empathy factor. The empathy factor here is classified as the inability of employees to understand and identify the feelings or situations of customers. Weiss and Cohen [26] argued that employee empathy and emotionality will affect the customer service experience. If customers get a bad empathetic response, it can impact customer satisfaction, which will cause customers to leave customer service with human agents. This research took These two factors as push factors for further analysis. For this reason, the researcher used the empathy and adaptability factors as the push factors of the research.

- H1. Push effect (empathy) has a negative effect on consumers' switching from human-to-AI customer service.
- H2. Push effect (adaptability) has a negative effect on consumers' switching from human-to-AI customer service.

2.3. Pull effects: responsiveness and accessibility

The term "pull factors" or "pull effects" describes a variety of external variables that draw in or influence consumers to choose a specific item or service. These factors include the benefits or advantages of the product or service, promotions or special offers, better product quality, or a better brand reputation. Customers migrate from the products and services they used before because of the emergence of interest in new products and services. This is also referred to as a product's alternative attractiveness [27], [28].

In this study, the pull factors come from the interaction in customer service using AI in the form of chatbots as agents, which is a two-way interaction between humans and digital agents. Chatbots provide customers with convenient choices to accomplish their objectives, such as obtaining information promptly. Chatbots virtually assist users like real hospital reception staff who provide total 24/7 assistance to users [29]. When consumers have issues with their healthcare demands, chatbots can respond faster than traditional healthcare providers and provide immediate assistance. The availability of chatbots not only offers immediate assistance but also addresses the issue of lengthy wait periods for responses to client inquiries. Responsiveness, in this case, refers to the chatbot's ability to provide consumer feedback. Based on the explanation, the responsiveness factor has become one of the pull factors for using chatbot technology today. AI-based customer service possesses distinct characteristics that set it apart from human-agent-based customer service. Through identification based on the accessibility theory, there are four accessibility features in digital media, namely accessibility, information retrieval, editability, and association [30]. Based on the accessibility theory, there is one factor that is closely related to chatbots, namely accessibility. Accessibility is the ease of contacting the service anytime and anywhere. For this reason, the researcher used the responsiveness and accessibility factors as the pull factors of the research.

- H3. Pull effect (responsiveness) has a positive effect on consumers' switching from human-to-AI customer service.
- H4. Pull effect (accessibility) has a positive effect on consumers' switching from human-to-AI customer service.

2.4. Mooring effects: trust

Within the PPM framework, mooring effects represent various factors that underlie the prevention behavior of an individual's attitude to change their behavior. These factors act as a foundation for individuals that make them stay with their current behavioral choices. Some factors that can influence the basis of an individual's attitude to not change are habits, loyalty, and trust in the use of product and service services. In addition, the emergence of factors such as lack of knowledge of new technology and bad experiences felt from the use of previous services become factors that underlie individuals to stick to the same habits [10]. Trust in the quality of currently good services can cause customers not to look for other alternatives to solve their problems. Tu *et al.* [31] provided an overview that in the minds of consumers, service satisfaction is an important factor that drives trust and loyalty. Trust felt by users or consumers towards a service or product will have a significant impact on the company. In the context of the healthcare industry, trust is a big thing and becomes an important factor in the foundation of consumer trust. For this reason, as a mooring effect, researchers chose trust as the main factor that underlies preventive behavior from an individual's attitude to changing their behavior.

- H5. Trust has a positive effect on consumers' switching from human to AI customer service.
- H5a. Trust positively moderates the relationship between the push effect and consumer switching behavior. The more trust in AI services, the weaker the relationship between the push effect (empathy) and switching from human agents to AI.
- H5b. Trust positively moderates the relationship between the push effect and consumer switching behavior. The more trust in AI services, the weaker the relationship between the push effect (adaptability) and switching from human agents to AI.
- H5c. Trust positively moderates the relationship between the pull effect and consumer switching behavior. The more trust in AI services, the stronger the relationship between the pull effect (responsiveness) and switching from human agents to AI.
- H5d. Trust positively moderates the relationship between the pull effect and consumer switching behavior. The more trust in AI services, the stronger the relationship between the pull effect (accessibility) and switching from human agents to AI.

Considering the numerous justifications presented above, the researcher concluded several hypotheses regarding the factors that trigger changes in customer behavior in the healthcare industry. To develop and illustrate the hypotheses regarding the factors that trigger changes in customer behavior in the healthcare industry, the researcher can construct a conceptual framework. Figure 1 presents a conceptual framework outlining the potential factors influencing customer behavior in the healthcare industry.

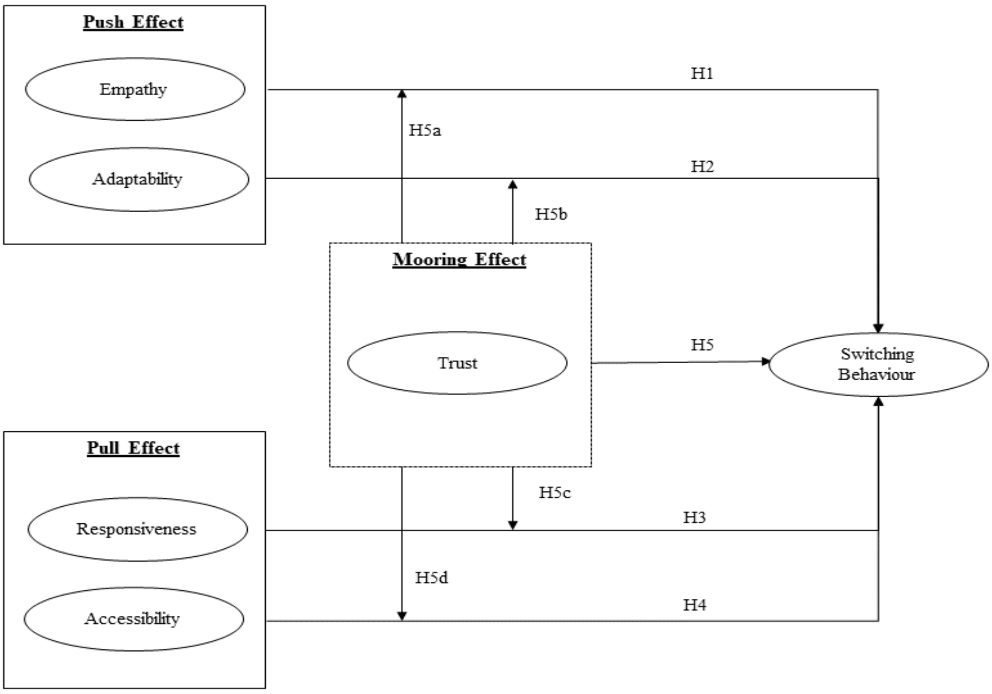

Figure 1. PPM research framework

3. METHOD

3.1. Design and participants

The appropriate research approach for this topic is descriptive and hypothesis testing. The descriptive approach is chosen because the characteristics and changes in customer behavior regarding customer service use in healthcare need to be described. In addition, the hypothesis testing approach is also chosen because the researcher needs to test the relationship between the variables that can influence customers' preferences for the type of customer service (chatbots/human agents) used.

The researcher did not intervene directly in the environment or variables under study, and the researcher will collect data from the actual situation that occurs in the customer environment (non-contrived) who have experience related to customer service in the healthcare industry. Therefore, the unit of analysis in this study is the customer, with the data collection period being sufficient to be done in one time period or cross-sectional because it is assumed that there is no change in variables, for example, changes from efforts to improve customer service quality.

The target population in this study is individuals who live in Indonesia who have used both AI-based chatbot services and human agents in healthcare services, which include services in hospitals, clinics, laboratories, pharmacies, or other digital health platforms in the past 1 year. Respondents from this study are healthcare users who have experience interacting with human service agents through agents of call centers and AI chatbot agents through health provider applications or instant messaging applications. The population in this study was taken from several healthcare customers, such as patients, family members, and general users of various healthcare services over 18 years old.

The sampling method in this research uses non-probability sampling methods-purposive sampling, namely, selected respondents have interacted with the healthcare industry using human agents and chatbots based on AI. The number of the population who have used AI-based chatbots in the healthcare industry is not known with certainty, so the determination of the number of samples can use the sample-to-item ratio formula, where the ratio must not be less than 1:5 [32], so the researcher sets the number of samples with a ratio of 1:5 with 24 questions, then the target respondents are 120.

3.2. Procedure

In this study, data was collected through an online survey. Respondents were selected from a number of online discussion communities and healthcare users in the researcher's environment. To ensure that the responses are more specific, respondents will be asked to complete and provide the name of the healthcare they use. In addition, respondents will be asked to answer several questions based on their experience interacting with customer service from human agents and AI chatbot services. To obtain targeted data, the researcher will provide two screening questions to be added at the beginning of the survey. These screening questions consist of questions about whether or not they have used customer service, both human and AI-based, and participants under the age of 18 are not allowed to be included in the sample. All items will be scored on a 5-point Likert scale, with possible responses from respondents' point of view from 1 (strongly disagree) to 5 (strongly agree). Because this study uses self-report measurement, there will be concerns related to biased results. All respondents will be made anonymous and confidential to maintain the respondents' comfort in filling out the survey.

3.3. Data analysis procedures

This study applies a quantitative method to examine the involvement of data collection and analysis of consumer behavior when interacting with chatbots and human agents in the healthcare industry. Partial least squares structural equation modeling (PLS-SEM) will be utilized for the analysis of the data gathered throughout the investigation, which is adopted for data analysis and model testing. PLS-SEM was chosen for several reasons, including the following. PLS is in line with the research objectives for prediction and theory development [33]. The study aims to further examine the intention of users to switch from human-based customer service to AI-based chatbots through the PPM framework. Therefore, PLS provides a suitable choice for theoretical development. We chose SmartPLS 3.0 for PLS analysis [34]. The analysis also involves two data measurements: the first is the outer model, and the second is the inner model. In the outer model, the researcher performs reliability and validity tests. Variable reliability can be measured with composite reliability (CR) and Cronbach's alpha (α). A construct is considered reliable when the CR value is greater than 0.70, and Cronbach's alpha value is greater than 0.60 [35]. While the construct is said to be valid when the average variance extracted (AVE) value is greater than 0.5 and the outer loading value is greater than 0.7 [36], [37]. In the inner model, the researcher will perform modeling using the R2 value in structural modeling. At the same time, R2 shows the prediction accuracy of the construct. Therefore, the R2 results of 0.75, 0.50, and 0.25 each describe the level of substantial, moderate, and weak predictive accuracy between constructs [38]. In the next stage, the researcher will test the hypotheses. The hypothesis is accepted if the t-value is higher than 1.96 (t-value >1.96) and the p-value is lower than 0.05 (p-value ≤0.05), and vice versa [36], [37].

4. RESULTS

4.1. Data analysis

In the outer model, we performed tests to assess the validity and reliability of the constructs. The AVE value assesses the validity of data and the loading factor values. The AVE number must be >0.5, while the loading factor value should >0.7. Table 1 displays the results of validity and reliability tests. The overall values of the indicators indicate that all the constructs are valid and reliable, as shown by the loading factor and AVE values. Furthermore, when looking at the values of CR and Cronbach's alpha used to measure construct reliability, they also indicate that the overall construct values have CR values greater than 0.7 and Cronbach's alpha values greater than 0.6.

Additionally, we conducted tests on the goodness of the model and hypotheses in the inner model. The goodness of the model is measured by the R2 value, while the alpha statistical value measures hypothesis testing. The Table 2 shows the value of the R-square that indicates the accuracy of the prediction. The R2 value for switching behavior is 0.742, meaning it has a moderate to substantial prediction accuracy. This indicates that the model explains 74% of the variance in switching behavior, suggesting that it is a moderately good predictor of this variable.

The research results from Table 3 show that in the push effect, empathy does not have a significant negative effect on customers switching from human agent services to AI-based agent services (P-value 0.681>0.05). Furthermore, adaptability has a significant negative effect on customers switching from services provided by human agents to services provided by AI-based agents (P-value 0.043<0.05). Then, in the pull effect, responsiveness has a significant positive effect on customers switching from services provided by human agents to services provided by AI-based agents (P-value 0.000<0.05). Next, accessibility has a significant positive effect on customers switching from services provided by human agents to services provided by AI-based agents (P-value 0.000<0.05).

In the mooring effect, trust does not have a significant positive effect on customers switching from services provided by human agents to services provided by AI-based agents (P-value 0.563>0.05). Furthermore, trust does not have a significant positive effect on moderating the relationship between the push effect (empathy) and customer switching behavior (P-value 0.886>0.05). The next hypothesis shows that trust does not have a significant positive effect on moderating the relationship between the push effect (adaptability) and customer switching behavior (P-value 0.209>0.05). Additionally, trust does not have a significant positive effect on moderating the relationship between the pull effect (responsiveness) and customer switching behavior (P-value 0.668>0.05). Then finally, trust also does not have a significant positive effect on moderating the relationship between the pull effect (accessibility) and customer switching behavior (P-value 0.999>0.05).

Table 1. Validity and reliability

Variable	Loading factor	Cronbach's alpha	Composite reliability	AVE
Accessibility		0.825	0.865	0.737
AC1	0.880			
AC2	0.889			
AC3	0.803			
Adaptability		0.824	0.835	0.587
AD1	0.708			
AD2	0.817			
AD3	0.728			
AD4	0.805			
AD5	0.767			
Empathy		0.844	0.863	0.679
EM1	0.806			
EM2	0.875			
EM3	0.793			
EM4	0.819			
Responsiveness		0.903	0.910	0.774
RS1	0.878			
RS2	0.860			
RS3	0.885			
RS4	0.896			
Switching Behavior		0.890	0.899	0.754
SB1	0.781			
SB2	0.894			
SB3	0.912			
SB4	0.880			
Trust		0.858	0.911	0.689
TR1	0.815			
TR2	0.897			
TR3	0.765			
TR4	0.839			

Table 2. The goodness of the model

	R-Square	Category
Switching behavior	0.742	Substantial

Table 3. The hypotheses testing

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics	P-values	Mark
H4: AC->SB	0.321	0.316	0.075	4.290	0.000	Accepted
H2: AD->SB	-0.248	-0.256	0.122	2.027	0.043	Accepted
H1: EM->SB	-0.037	-0.028	0.091	0.411	0.681	Rejected
H3: RS->SB	0.436	0.432	0.096	4.537	0.000	Accepted
H5: TR->SB	-0.031	-0.027	0.054	0.579	0.563	Rejected
H5b: TRxAD->SB	0.085	0.076	0.067	1.257	0.209	Rejected
H5a: TRxEM->SB	-0.012	-0.003	0.082	0.143	0.886	Rejected
H5c: TRxRS->SB	-0.047	-0.047	0.109	0.430	0.668	Rejected
H5d: TRxAC->SB	0.000	-0.004	0.108	0.001	0.999	Rejected

**Note: AC= accessibility, AD= adaptability, EM= empathy, RS= responsiveness, T= trust, SB= switching behavior*

The research findings indicate that customer switching behavior is influenced by the low driving force of adaptability from human agents and the attractiveness of responsiveness and accessibility from chatbots. The push and pull effects show that in the healthcare industry, customer switching behavior to use digital-based services through chatbots is driven by speed and convenience in contacting customer service without having to speak through the phone or make direct visits. However, the mooring effect reveals that trust plays a less significant role in influencing customers to switch from human-agent services to AI-based ones. This is evident in the lack of a significant positive impact of trust on customer switching behavior, even when considering its moderating effects on the push and pull factors. The details regarding the PLS-SEM path model are shown in Figure 2.

4.2. Demographic

In this study, we also conducted an identification of the demographic data of the respondents. The identifying respondent demographic data aims to understand the profile of respondents who participated in the study. This demographic data includes several aspects, such as age and gender, which can provide insight into the characteristics of respondents and their relevance to the research topic. Respondent demographics are shown in Table 4.

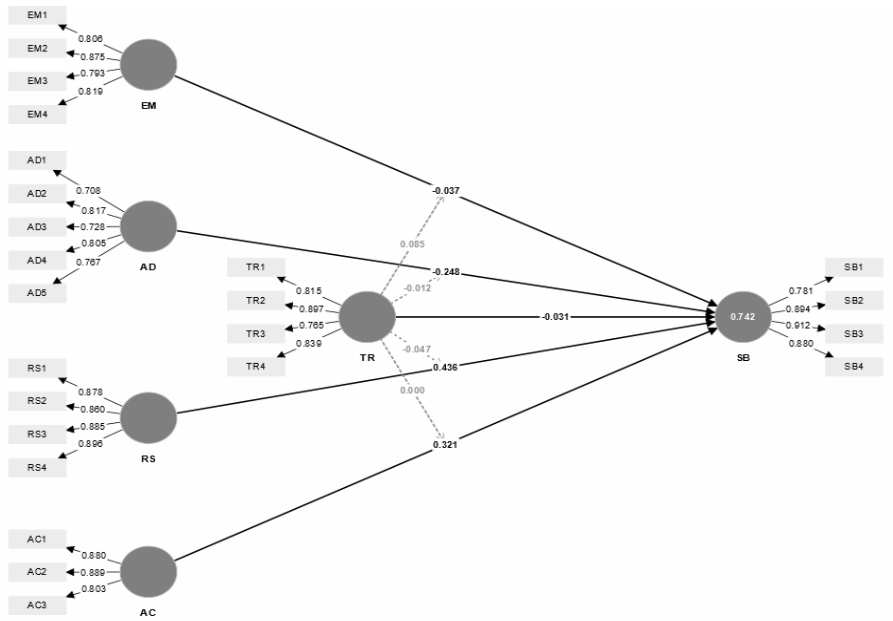

Figure 2. PLS-SEM path model

Table 4. Demographic respondents

Measure	Items	Total	Percentage
Gender	Male	61	41%
	Female	86	59%
Age	18-25	28	19%
	26-30	67	46%
	31-35	26	18%
	36-40	24	16%
	>40	2	1%
AI Chatbot Service	Government institution X	5	3%
	Digital health application X	14	10%
	Healthcare center A	93	63%
	Healthcare center B	11	7%
	Healthcare center C	7	5%
	Healthcare center D	15	10%
	Healthcare center E	2	1%

4.3. Discussion

The main discoveries can be summarized as follows. Firstly, the push effect has a detrimental influence on behavioral change. Bock *et al.* [39] argue that the absence of empathy and adaptability in service agents has a negative impact on customer satisfaction. When customers feel that customer service representatives cannot understand their requirements and fail to go beyond what is necessary to satisfy them, their satisfaction levels decrease. Consequently, this dissatisfaction influences customers' preference for human agent services. In this study, although low empathy of human agents did not significantly affect the push effect, adaptability had a stronger influence. Customers tend to prioritize qualities such as speed, accessibility, and service flexibility (e.g., 4/7 availability). Since customer service provided by human agents often involves waiting for assistance, customers prefer switching to AI chatbots.

The second discovery emphasizes the beneficial influence of the pull effect on changing behavior, particularly about accessibility and responsiveness. The effects arise from AI chatbots providing instant support at any time and anywhere, offering customers links to access pertinent information, address problems using text or symbols, and receive customized responses. The results are consistent with prior studies. Tseng *et al.* [40] propose that providing quick responses and pertinent information via instant messaging platforms can improve customer satisfaction and loyalty, strengthening customer engagement. Fang [41] states that customers are more likely to intend to utilize a product when they access specific connections through media platforms.

Third, trust did not significantly impact customers' willingness to switch to AI chatbots. While initial analysis suggested that trust might positively moderates both the push and pull effects driving customer behavior change toward AI chatbots, further examination revealed that this relationship was not statistically significant. Nonetheless, these findings indicate a general openness among customers to embrace AI chatbots for customer service, suggesting a perception of their capability in addressing customer concerns.

5. CONCLUSION

This research indirectly reveals customers' desire to resolve their complaints or issues quickly. This is evidenced by the significant findings of the push effect and adaptability, which influence customers' preferences for customer service in the healthcare industry. In addition, the pull effects of responsiveness and accessibility also significantly impact this preference. Surprisingly, trust in chatbots does not significantly influence the push and pull effects when customers are required to choose. Therefore, customers are more concerned with receiving customer service that can always assist them in a relevant manner, with quick responses, and can be accessed anytime and anywhere. In the end, customers show a high intention to change their behavior by migrating from human-agent customer service to AI chatbot customer service in the healthcare industry. This research initiates an understanding of customer behavior toward customer service channels in the healthcare industry.

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Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dwi Fajar Yulianto	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Titik Pratiwi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Fatih Akbarul Irsan	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Faranita Mustikasari	✓	✓		✓	✓	✓				✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data generated and analyzed during this study are available from the corresponding author upon reasonable request. Due to potential privacy concerns or proprietary agreements, certain datasets may require further ethical or legal considerations before dissemination. Requests should be directed to the corresponding author's contact details.

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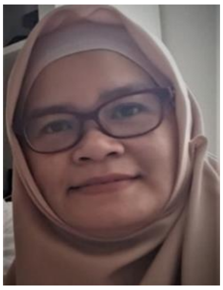

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