Understanding Heterogeneity in CRM Chatbot User Preference

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Abstract

Nowadays, chatbots have been widely used as one of the companies' operational CRM solutions, due to their efficiency in handling many customer requests simultaneously. Based on previous studies, users can have different preferences regarding how to interact with a chatbot. By conducting a literature study from more than 36 relevant works of literature, this research explores four chatbot attributes that have trade-offs on user preferences: chatbot appearance, conversational style, chatbot proactive behavior, and user input control. The first attribute relates to how a chatbot is shown to the user. Alternatives to these visual social cues include; brand/company logo, avatar, and human photograph. The conversational style talks about verbal social cues, which is how information is conveyed by a chatbot using certain language variations. This attribute is based on two main dimensions in social judgment studies, which are warmth and competence. The third attribute relates to how a chatbot behaves, whether proactive or reactive. Finally, the last attribute talks about which method that users like to enter messages, whether by using quick replies or a free-text field. Then, we propose that heterogeneity in chatbot user preference is related to user characteristics, such as demography, experience in using chatbots, and personality.

Keywords
Chatbot, Customer Relationship Management, Preference Heterogeneity, and Big Five Personality Model

1. Introduction

Customer relationship management is a crucial part of the company's integral system. CRM is “the entire process of building and maintaining profitable customer relationships by delivering superior customer value and satisfaction” (Kotler & Armstrong, 2018, p. 38). Customers can feel superior value if the benefits and prices of products/services considered by customers are better than those of competitors. Meanwhile, customer satisfaction can be achieved if the services provided by the company can meet customer expectations (Kotler & Armstrong, 2018). In return, fulfilled customer expectations and satisfaction can generate financial gains for the company. Loyal/engaged customers can spend money 90% more often and 60% higher (on each purchase) than regular customers, so that in one year the customer base can be worth three times more (Pozin, 2018). Technological advances in the current digital era have also changed customer expectations for the services provided by the company. 75 % of consumers want instant online services in just five minutes (Duncan et al., 2016). One of the technologies that companies can use to meet this demand is chatbots. Um et al. (2020, p. 3) define a chatbot as an "automated system that emulates person-to-person dialogue through text or voice messages".

In the context of CRM, a chatbot can be used by companies to interact with customers using their everyday language. Some examples of its use are; ordering, question and answer (Q&A), customer support, customer engagement, and providing advice/recommendations related to a product/service (Bavaresco et al., 2020). Business sectors that have used chatbots include; trade, finance, restaurants, health, telecommunications, and tourism (Bavaresco et al., 2020). The advantage of chatbots over human agents is that accessible for customers at any time (Artificial Solutions, n.d.; Sweezey, 2019). Moreover, chatbots are fast, accurate, able to handle multiple requests simultaneously and comply with existing regulations (accountable and transparent) (Artificial Solutions, n.d.). Meanwhile, a human agent generally cannot serve many consumers at the same time.

Along with the development of chatbots globally, much academic research on chatbots has emerged, especially in recent years. Research on chatbots covers various knowledge domains, ranging from computing, technology, ergonomics, psychology, to marketing. Previous researchers have tried to understand what factors can influence user perception and acceptance of chatbot technology. For example, Chung et al. (2020) examine the effect of chatbot marketing efforts on customer satisfaction in the context of luxury brands. Marketing efforts consisting of interaction, entertainment, trendiness, customization, and problem-solving can increase user satisfaction through the intermediary of communication quality consisted of accuracy and credibility. In addition, Sanny et al. (2020) analyze what customer satisfaction factors can affect chatbots acceptance in Indonesia. In this exploratory study, four latent factors were obtained, namely, usefulness, brand image, personality, and ease of use (Sanny et al., 2020). These factors still need to be translated into more concrete chatbot design attributes. Therefore, some researchers are more specific in studying the effect of chatbot design attributes in improving interaction quality between humans and such technology.

However, there are some trade-offs found in the chatbot attribute research. According to Merriam-Webster's Learner's Dictionary (2021), a trade-off can be defined as "a situation in which you must choose between or balance two things that are opposite or cannot be had at the same time". Several chatbot design attributes have trade-offs on user preferences. Research on these chatbot attributes often produced different findings. Some examples are chatbot appearance, chatbot conversation style, chatbot proactive behavior, and user input control. These attributes will be explained further in a later section. Given the trade-offs of several alternatives of chatbot attributes, companies that want to implement chatbots in the CRM process need to consider the chatbot design that is most suitable for their customers. This is because the user acceptance level of chatbots can be influenced by their preferences in using that technology. Meanwhile, chatbot attribute preferences between customer groups may differ, as revealed in Johannson and Kröger's (2019) research. This is natural, considering that customer groups/segments can have different characteristics and needs. This way, companies can customize specific chatbot attributes for each targeted customer segment.

For example, user personality might influence the preference structure of chatbot design attributes. As in research by Roy and Naidoo (2021), customers' personalities in the form of different time orientations can influence chatbot conversational style preferences. They reveal that a match between the chatbot's conversational style and the customer's time orientation can increase positive attitudes and purchase intentions. In line with this, Mehra (2021) suggests further research in this area (human-chatbot-interaction) to consider the user's personality that can influence their preferences and perceptions of chatbot personality. In addition to personality, other user characteristics that can generate insight about user preference heterogeneity are demographics and experience in using chatbots. In terms of demographics, it is necessary to examine whether young and old customers have different preference structures, considering that both have different attitudes and experiences towards technology. Meanwhile, users who have experience in interacting with chatbots might better understand the capabilities and consequences of chatbot attributes, so they can have more mature preferences.

Thus, this study aims to discuss four chatbot attributes that have trade-offs in shaping user preferences. Moreover, we also discuss several factors that can be related to the heterogeneity of user preference structures. Then, further research actions are proposed to analyze this empirically.

2. Literature Review

2.1. Chatbot

Chatbots are classified as conversational agents, namely, software that can carry out conversations with human users, by processing input in the form of natural language into output in the form of natural language (Griol, Carbó, & Molina, 2013). A chatbot system can also be defined as "a software program that interacts with users using natural language" (Ciechanowski et al., 2019, p. 540). Meanwhile, Um et al. (2020, p. 3) define a chatbot as "an automated system that emulates person-to-person dialogue through text or voice messages". Based on the descriptions above, chatbots can be defined as software that can imitate conversations with humans automatically, either through text or voice media. Furthermore, Araujo (2018) distinguishes conversational agents into two types, namely embodied conversational agents (ECAs) and disembodied conversational agents (DCAs). The difference between the two is that ECAs have a physical representation of a virtual body or face that can move, for example in the form of a robot or animated image. Meanwhile, DCAs representations are only static images or there are not any at all, such as chatbots commonly found on websites and messaging applications. Referring to Araujo (2018)'s explanation of this difference, this present research will focus on DCA-type conversational agents based on text media. This is because the chatbots that are widely used in the company's customer service nowadays are currently still based on text media.

How chatbots work can be understood by looking at the chatbot architecture diagram described in the Adamopoulou and Moussiades's (2020) paper. Broadly speaking, a Chatbot consists of the following components: User Interface Component, User Message Analysis Component, Dialog Management Component, Back-end, and Response Generation Component (Adamopoulou and Moussiades, 2020). Meanwhile, this study focuses on chatbot attributes that play a direct role in chatbot-human interactions. By referring to the human-centric design paradigm, the design attributes of the chatbot are expected to increase user satisfaction and experience.

2.2. The Computers Are Social Actors (CASA) Paradigm

Some studies that investigate human-chatbot interaction use the Computers Are Social Actors (CASA) paradigm. The paradigm proposed by Nass et al. (1994) explains the human tendency to apply social rules when interacting with computers like interacting with other humans in certain social situations. Such interactions can be caused by the presence of human cues/attributes in computer entities, such as personality (Nass et al., 1995).

In another word, the social responses from the user can be stimulated by social cues or computer characteristics that resemble humans, such as gender (Nass et al. 1994) and personality (Nass et al., 1995). Users will respond to computers like humans, even though the person is aware that computers have no soul (Nass et al., 1995). This matter can be called ethopoeia, namely the "assignment of human attitudes, intentions, or motives to non-human entities" (Nass et al., 1995, p. 225). The process of forming social responses can be explained using a diagram from Feine et al. (2019, p. 142) in Figure 1.

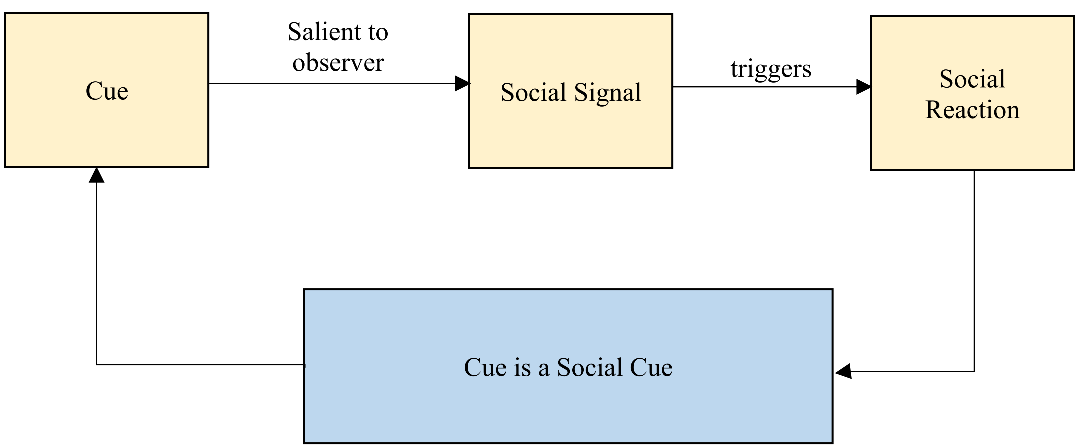

Figure 1. The process of forming social reactions (Adapted from Feine et al., 2019, p. 142)

In the context of a chatbot as a conversational agent, a cue is a design or feature of a chatbot that stands out for users and shows certain information (Feine et al., 2019). Then, these cues can be captured by the human mind as a social signal, namely "conscious or unconscious interpretation of cues in the form of attributions of mental state or attitudes towards the conversational agent" (Feine et al., 2019, p. 141). These social signals can then trigger a social reaction from users as in interacting with other humans, either in the form of emotional, cognitive, or behavioral reactions. More specifically, chatbot cues that can trigger users' social reactions are called social cues (Feine et al., 2019).

Thus, the CASA paradigm can be applied to chatbots, which are a sort of computer program. Moreover, chatbot technology can imitate interpersonal conversations between humans. Therefore, it is important to investigate what kind of chatbot social cues can trigger positive social reactions from users, which in turn can increase user satisfaction in using the technology. These social cues can be embedded in chatbot attributes such as chatbot appearance, chatbot conversation style, and chatbot behavior.

2.3. Social Judgment

Various situations such as social inequality, globalization, cultural differences, and immigration encourage people to understand and judge others (Fiske, 2018). Based on research in psychology, social judgments made by humans on other individuals or groups are based on two main dimensions, namely warmth, and competence (Fiske et al., 2006). These two dimensions included in the stereotype content model (SCM) framework (Fiske et al., 2002) are considered valid, reliable, and can be generalized to various cultures and research contexts (Fiske, 2018).

The warmth dimension shows the human perception of the intentions possessed by other individuals or groups (Fiske et al., 2002; Fiske et al., 2006) The warmth dimension consists of (ordered by priority); “warm, trustworthy, friendly, honest, likable, and sincere” traits (Fiske, 2018, p. 68). Meanwhile, the competence dimension describes how capable other people are in realizing such intentions (Fiske et al., 2002; Fiske et al., 2006). This dimension consists of the nature of “competent, intelligent, skilled, and efficient, as well as assertive and confident” (Fiske, 2018, p. 68).

Social judgments on the two dimensions above can influence the feelings and behaviors shown by that person to others (Cuddy et al., 2011; Fiske, 2018). Although the two dimensions above are expected to be equally high in value, sometimes they do not have a high correlation (Fiske, 2018), even the correlation can be negative (Cuddy et al., 2011). The condition in which one dimension has a high value and another has a low value is called an ambivalent group/quadrant (Fiske, 2018). Moreover, there can be a contrast/compensation effect when someone compares two individuals/groups, for example, one individual/group is rated higher on warmth dimension but gets a lower rating on the competence dimension, and vice versa (Cuddy et al., 2011; Fiske, 2018). The compensation effect is also related to how a person maintains an impression. Interestingly, someone who wants to appear competent tends to decrease warmth, and vice versa (Holoien & Fiske, 2013).

Based on previous studies, the weight of a person's assessment can be more inclined to one dimension (Cuddy et al., 2011; Roy & Naidoo, 2021). Which dimension is considered more important is situational (Cuddy et al., 2011). Then, personality such as individual time orientation also influences preferences for these two dimensions (Roy & Naidoo, 2021). Based on the descriptions above, someone should be strategic in managing the dimensions they want to highlight, whether the dimensions of warmth or the dimensions of competence.

Interestingly, a person's social judgment does not only apply to other humans but can occur to various forms of robots. Roy & Naidoo (2021) prove that the dimensions of warmth and competence can be reflected in the chatbot's conversational style and influence user evaluations (whether the chatbot is warm or competent). In addition, Peters et al. (2017) incorporate the dimensions of warmth and competence into the non-verbal behavior of an educational robot. The given non-verbal behavior can affect students' social judgment of the robot. Then, the two dimensions of SCM can influence a person's preference in choosing an artificial intelligence system (Gilad et al., 2021). These findings are in line with the previously mentioned CASA paradigm, that humans can treat computers/robots as social entities, including giving social judgments.

3. Method

The research begins with getting insights into the current development of chatbots in the industry. This is done by reading industry reports, textbooks, articles, news articles, and interviewing one of the chatbot implementers in an Indonesian telecommunication company. Next, we conduct a literature study to examine the relevant theories and trade-offs among previously studied chatbot attributes. Then, we could identify the gaps from these two perspectives.

The literature study is carried out by searching for related keywords on scientific article database pages such as Google Scholar and ScienceDirect. Then, more than 36 relevant works of literature were screened and studied. Complementary theories are also obtained through academic textbooks. This study focuses on four chatbot attributes related to human-chatbot interaction, namely, chatbot appearance, chatbot conversation style, chatbot proactive behavior, and user input control. Other theories studied include chatbot's social cues (within CASA paradigm), social judgment dimension, and the Big Five personality model to link chatbot attribute preferences with user characteristics.

This conference paper only focuses on discussing the research variables that form the basis of the conceptual model. The empirical study will be conducted at the following research stage using conjoint analysis and latent class analysis. Using both methods, potential chatbot users will be grouped into segments that have a similar preference structure. Then, the characteristics of each segment will be analyzed using a profiling technique. Further validation will be carried out by prototyping a chatbot based on the preferences found in empirical study and then testing it on related user segments.

4. Discussion

4.1. Chatbot Attributes

The four chatbot attributes considered in this study are as follows:

4.1.1. Chatbot Appearance

This design attribute can be classified into the visual cues category in the chatbot social cues taxonomy by Feine et al. (2019). Chatbot appearances such as the use of photos/avatars and names that resemble humans (anthropomorphic) are expected to increase the perception of anthropomorphism, as in Araujo's research (2018). Meanwhile, research by Go and Sundar (2019) is unable to find a direct effect of the use of visual anthropomorphic cues on the humanness perceptions in the form of similarities between the chatbot and the user. In these conditions, the similarity perception can increase if chatbots are introduced as human agents. However, the use of anthropomorphic visual cues can compensate for the effect of low message contingency or interactivity, and vice versa (Go and Sundar, 2019).

However, the appearance of a conversational agent that is too human-like can cause an uncanny valley effect for users, namely feelings of disgust, horror, or discomfort towards a technology (Ciechanowski et al., 2019). Ciechanowski et al. (2019) argued that this feeling can arise due to conflicts in the user's mind regarding the identity of the conversational agent which seems to disturb the uniqueness of human identity. Therefore, chatbot designers and corporate stakeholders need to pay attention to trade-offs in presenting chatbot appearances.

In addition to avatars and human photos, another form of chatbot appearance is the use of brand/company identity in the form of a logo and brand/company name. However, no research has been found that discusses this form of appearance. Therefore, this study wants to expand the previous research by considering three types of chatbot appearances, namely the use of avatar/cartoon-like image, human photo, and brand/company logo.

4.1.2. Chatbot Conversation Style

Conversational style can be classified into the verbal cues category in the chatbot social cues taxonomy by Feine et al. (2019). This attribute discusses how information is conveyed by a chatbot (Roy & Naidoo, 2021), by using variations of words/languages that have certain meanings (Feine et al., 2019). As with interpersonal conversations in general, chatbot conversation styles can be designed in various ways. Two examples are warm versus competent conversational styles (Roy and Naidoo, 2021). The conversational style can be manipulated by the choice of words used by the chatbot. A warm conversational style reflects friendly and helpful traits, while a competent conversation style reflects capable and expert traits (Roy and Naidoo, 2021). These styles reflect the two dimensions of social judgment/SCM mentioned earlier.

Interestingly, the effect of chatbot conversational style on attitudes towards a brand and purchase intentions is also influenced by the customer time orientation. Present-oriented customers tend to prefer a warm conversational style over competent. Meanwhile, future-oriented customers tend to prefer a competent conversational style (Roy and Naidoo, 2021). Through this research, we can learn that user preferences regarding chatbot conversation styles can vary and are also influenced by the user's personality.

Continuing from the previous research by Roy and Naidoo (2021), differences in user preferences for chatbot conversational styles can be viewed from other personality dimensions, for example using the Big Five model. In addition, it is necessary to examine how this attribute is combined with other social chatbot attributes in the preference structure of each customer segment.

4.1.3. Chatbot Proactive Behavior

Chatbots can be proactive or reactive in delivering messages to users. Based on the two premises of a proactive system proposed by Salovaara and Oulasvirta (2004), a proactive chatbot is programmed to take some initiatives in providing messages without being asked directly by the user. The message is in favor, or pro, to the user (Salovaara & Oulasvirta, 2004). Meanwhile, reactive chatbots tend to deliver messages only based on what the user is asking or ordering.

Both types of behavior have trade-offs. On the one hand, proactive chatbots can provide valuable relevant information to users, maintain conversational efficiency, and give the impression of good service (Følstad and Halvorsrud, 2020). On the other hand, a chatbot's proactive attitude can also give a bad impression. In the study of Liao et al. (2016), the use of a proactive personal chat agent is considered disturbing for some people, which can then reduce the positive impression and user experience. In addition, being proactive can be seen as intruding on one's privacy (Følstad and Halvorsrud, 2020).

On the other hand, the chatbot's reactive behavior can make users feel in control of the chatbot, but they may miss out on useful information (Følstad and Halvorsrud, 2020). When addressing the trade-offs above, companies need to understand user characteristics (Liao et al., 2016). This is because users can have diverse preferences for proactive behavior (Følstad and Halvorsrud, 2020). Thus, companies can design appropriate and targeted chatbot behavior.

4.1.4. User Input Control

Users can enter messages by several methods. Two of them are through free-text field or quick replies (Duijst, 2017). By using the free-text field, users can type messages freely as when sending a text on messenger. Meanwhile, quick replies are message recommendations provided by the system to choose from, usually by clicking on that option.

These two input methods have trade-offs. On the one hand, quick replies have the advantage of saving time and minimizing input errors (Duijst, 2017). In addition, some of the research participants in the research by Valério et al. (2020) find the quick reply option easy to use and can help users understand the chatbot's capabilities. In line with this, Meerschman and Verkeyn’s (2019) research respondents commonly prefer quick replies as the main input method. This quick reply feature is included in the Attractive attribute category in the Kano model built by researchers (Meerschman and Verkeyn, 2019).

However, some users in other studies feel that quick replies provide limited options (Duijst, 2017). Quick replies are not like usual conversations because the user seems to just browse the navigation menu (Valério et al., 2020). Therefore, the quick reply option makes the chatbot feel less human to some users. In line with this, the research of Diederich et al. (2019) shows that the use of quick replies can reduce the perception of humanity (humanness) and social presence without significantly increasing service satisfaction.

On the other hand, the free-text field can provide flexibility for users to type any message, so that it feels like a natural conversation (Duijst, 2017). Some of the participants in the study of Valério et al. (2020) also prefer to chat with chatbots than using the quick reply option. As previously mentioned, the study of Diederich et al. (2019) shows that the use of free-text fields without quick replies has advantages in terms of human perception and social presence.

However, this method is prone to failures or errors, for example, chatbots do not understand user intentions and input (Duijst, 2017; Meerschman and Verkeyn, 2019). Chatbot failure can make users feel difficult (Valério et al., 2020) and frustrated (Meerschman and Verkeyn, 2019), especially if they must repeat the conversation from the beginning. Furthermore, chatbots containing errors can reduce the perception of anthropomorphism and reduce the desire to adopt the technology (Sheehan et al., 2020). Thus, from the user's perspective, there is a trade-off between efficiency versus anthropomorphism, with limitations in the form of limited options in the quick replies method and error-proneness in the free-text field method.

In addition, there is also a combined method that can compensate for the nature of the two input methods above (Duijst, 2017). However, this method is considered more technically difficult. This is because the chatbot must be able to track the structure of the conversation with the user while still understanding and remembering the varied user answers (Duijst, 2017). Therefore, chatbot designers and corporate stakeholders need to carefully weigh the trade-offs of the user input method to be applied.

4.2. Descriptive Variables

As explained earlier, a market may consist of user segments that have different characteristics and needs. In the context of this research, each segment of chatbot users can have different preferences for chatbot attribute design. Thus, it is also necessary to consider factors that can explain the preference differences between user segments. These factors are called descriptive variables.

The first factor considered to be a descriptive variable is user personality. As mentioned earlier, Roy and Naidoo (2021) show that different customer personalities can influence preferences for chatbot conversation styles. Thus, we can also expect user personality to influence the preference of other chatbot attributes. The first definition of personality is "a set of distinguishing human psychological traits that lead to relatively consistent and enduring responses to environmental stimuli including buying behavior" (Kotler & Keller, 2016, p. 185). Meanwhile, Kotler & Armstrong (2018, p. 168) define personality as "the unique psychological characteristics that distinguish a person or group". Referring to the two expert definitions above, personality can be interpreted as a collection of psychological traits that distinguish a person or group from other people/groups in responding to the environment, while generally being consistent and durable.

In this study, the personality model used to explain differences in customer preferences is the Big Five model, which consists of Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience (John & Srivastava, 1999). We choose this model because it describes five main trait dimensions that can be replicated and generalized to many varieties of samples and test methods (John & Srivastava, 1999). The Big Five model is also used in Mehra's (2021) research but with the context of the chatbot personality. Therefore, it will be interesting to study the use of the Big Five model in the context of user personality when operating a chatbot. The dimensions of the Big Five model are presented in Table 1.

Table 1. Big-Five Personality Dimension (John & Srivastava, 1999, p.121; Mehra, 2021, p.2)

No.	Dimension	Explanation
I	*Extraversion*	Dimension of personality that is energetic to the material and social world and supports sociable, friendly, active, assertive, and positive emotions.
II	*Agreeableness*	Dimension of personality that is prosocial- and communal-oriented and supports altruistic, likable, cooperative, polite, soft-minded, and trusting traits.
III	*Conscientiousness*	Dimension of personality that is task- and goal-oriented, by controlling social impulses and supporting the nature of responsibility, obedient, readiness, full of planning, and understand the consequences of what is done.
IV	*Neuroticism*	Dimension of personality that supports negative emotions such as worry, tension, sadness, and anxiety in stressful environments.
V	*Openness to Experience*	Dimension of personality that supports the desire to try new things, is open to new thoughts, and can describe the breadth and complexity of one's experiences.

Meanwhile, the second factor used as a descriptive variable is demographics. According to Kotler and Armstrong (2018, p. 96), demography is “the study of human populations in terms of size, density, location, age, gender, race, occupation, and other statistics”. Demographic factors are chosen because they can reflect differences in consumer needs, desires, and levels of use of a product (Kotler and Armstrong, 2018). Demographic aspects used in this study include location, age, and gender.

Then, the third factor used as a descriptive variable is the experience in using a chatbot. In terms of marketing segmentation, it can be included in the behavior-based segmentation variable (Kotler & Armstrong, 2018). Behavior-based segmentation variables distinguish users based on their level of knowledge, use, attitude, or response to the product or service provided (Kotler and Armstrong, 2018). In the context of this research, the experience of using chatbots includes the type of chatbot used, the level of chatbot usage (how often they used chatbots before), and the motives for using chatbots. Thus, this research model can be depicted in Figure 2.

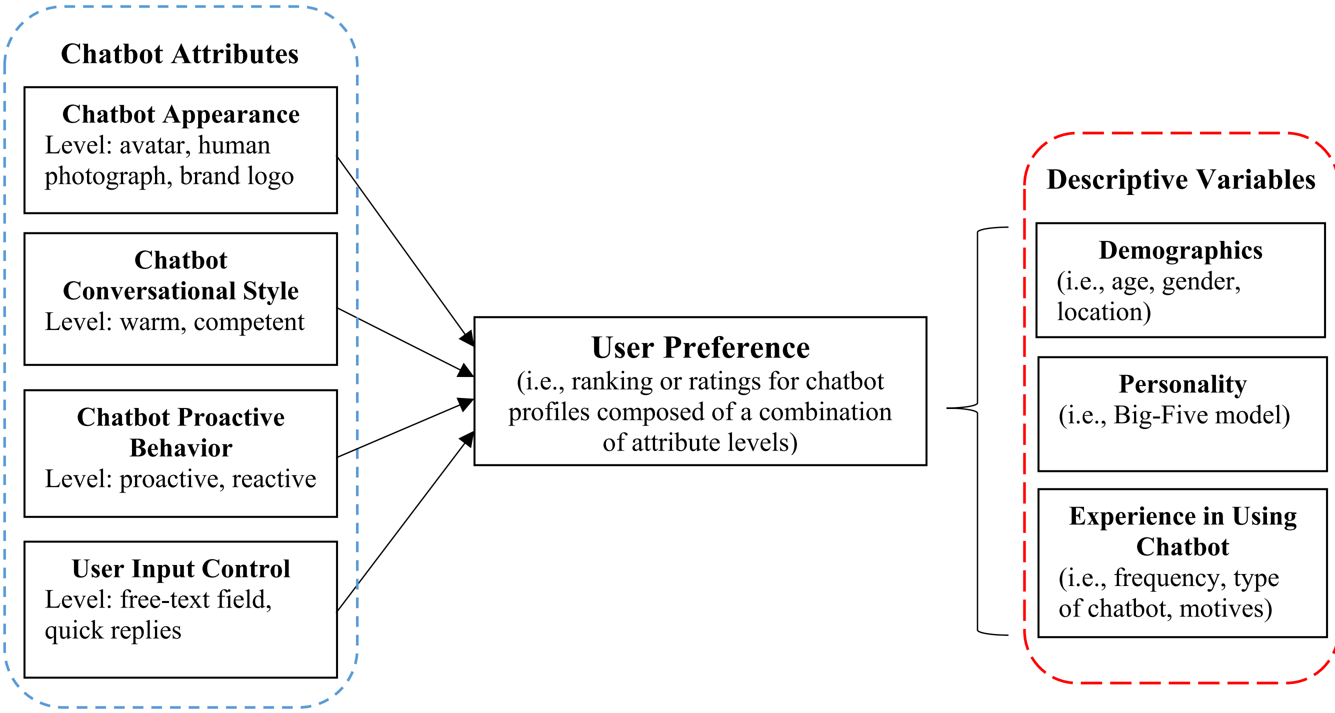

Figure 2. Conceptual model of chatbot attribute preference heterogeneity in this study

5. Next Research Step

The structure of consumer preferences for the attributes of a customer service chatbot can be analyzed empirically using conjoint analysis. Conjoint analysis is a method to determine the importance level of the attributes of a product/service along with the utility value of each level in it perceived in the minds of consumers (Malhotra, 2020). The conjoint analysis uses the basic assumption that consumer ratings and preferences for a product/service are built from a combination of separate attribute values (Hair et al., n.d.). The measure of an individual preference can be expressed as a utility value (Hair et al., n.d.). In the context of this research, the four chatbot attributes mentioned earlier are used as conjoint analysis attributes, and the design alternatives for each attribute are called levels. By using conjoint analysis, researchers can determine which chatbot design is the most preferred for each attribute and the relative importance of each chatbot attributes. Details on conjoint analysis can be read in Hair et al. (n.d.) and Malhotra (2020).

Using traditional full-profile conjoint analysis, respondents evaluate a series of "product profiles" composed of several attributes with corresponding levels (Hair et al., n.d.). In this study, chatbot profiles can be conveyed in the form of screenshots of chatbot conversations with customers consisting of the four chatbot attributes mentioned earlier. Using chatbot conversation screenshots can make it easier for customers to understand conversation scenarios that resemble real situations. An example of this is presented in Figure 3.

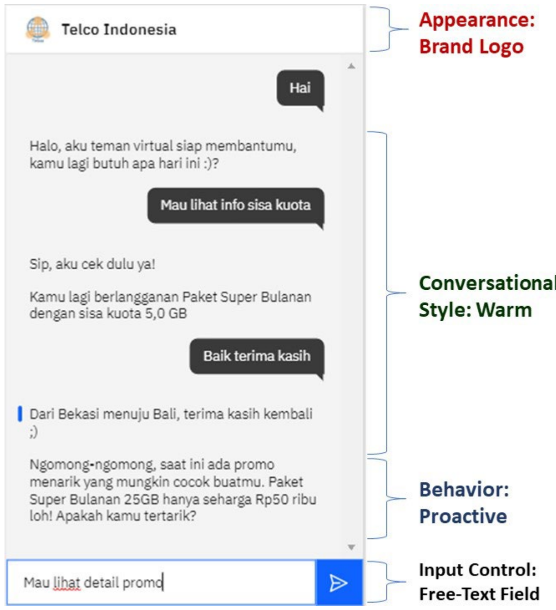

Figure 3. Example of chatbot conversation screenshot as a conjoint profile (written in Bahasa Indonesia)

The simple conjoint analysis model can be expressed through the following mathematical equation (Malhotra, 2020, p. 675). The conjoint analysis aims to estimate the parameter α_{ij}.

$$U(X) = \sum_{i=1}^{m} \sum_{j=1}^{k_i} \alpha_{ij} x_{ij} \qquad \text{(Equation 5.1)}$$

Explanation (Malhotra, 2020, p. 675):

- U(X) = the total utility value of a profile, indicating the respondent's preference
- α_{ij}= the value of utility/part-worth owned by the jth level (j=1,2,.., k_i) of the ith attribute (i=1,2,..,m)
- k_i= The number of levels of the ith attribute
- m = number of attributes
- x_{ij}= 1, if the profile contains the jth level of attribute i
- x_{ij}= 0, if the profile does not contain the jth level of attribute i

Two types of assessment methods include ranking and rating methods. In the ranking method, respondents sort several profiles (or pairs of attribute levels in the pairwise approach) from the most preferred to the least preferred. Meanwhile in the rating method, respondent gives a score to each profile following a certain scale, for example, a Likert scale of 1-9 or 1-10 (Hair et al., n.d.; Malhotra, 2020). Meanwhile, the estimation method of conjoint analysis depends on the preference measurement used. If the preference measure used is ranking, the researcher can perform a modified analysis of variance (ANOVA) using a computer program such as MONANOVA (Monotonic Analysis of Variance) or LINMAP. Meanwhile, researchers can use multiple regression methods or multinomial logit models for metric preference measures (Hair et al., n.d.).

Although the analysis can be performed at the aggregate level, the simple conjoint analysis does not take into account the heterogeneity of the preference structure (i.e., there may be user segments that have different preference structures). One way to identify these hidden/latent segments is to use the latent class method (Desarbo et al., 1992;

Desarbo et al., 1995). This method can be used in conjoint analysis, as done by Steiner et al. (2016). Steiner et al. (2016) studied the preference differences of game console system customers and found four distinct main segments.

The advantage of the latent class method is that it can estimate the part-worth value of each identified segment along with its membership list simultaneously (Desarbo et al., 1992). In the latent class method, the respondent's membership in a segment is not stated absolutely but is probabilistic. In other words, each respondent has a probability of membership in each segment. The greater the probability value, the more suitable the preference structure of a respondent with that segment (Desarbo et al., 1992; Desarbo et al., 1995).

Furthermore, profiling is carried out on each user segment using descriptive variable data consisting of personality, demographics, and experience in using chatbots. Several questionnaire-based instruments can be used to measure the personality construct of the Big-Five model, such as the Big Five Inventory (BFI) (John et al., 1991), BFI-10 (Rammstedt and John, 2007), Ten Item Personality Inventory (TIPI) (Gosling et al., 2003), etc. The total scores of the items for each of the Big Five personality dimensions can be averaged for each segment. What is interesting to note is the possibility of a segment excelling on one or more of the Big Five dimensions compared to other segments. The average value of personality dimensions between segments then can be compared using the Chi-Square test to see the significance of these differences.

6. Conclusion

This paper discusses four attributes involved in human-chatbot interactions, namely, chatbot appearance, chatbot conversation style, chatbot proactive behavior, and user input control. Each attribute consists of several design alternatives with trade-offs that can affect user preferences in interacting with the technology. In addition, users may consist of segments that have different preference structures. The heterogeneity of this preference structure can be analyzed empirically using conjoint analysis and latent class in the next research steps. Furthermore, the characteristics of each segment can be profiled using descriptive variables such as Big-Five personality, demographics, and experience in using a chatbot. The results of this study can be used for industry practitioners to adjust the chatbot design to the characteristics of the targeted customers. It aims to increase satisfaction in using CRM-related chatbots.

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