Journal of Customer Behavior and Technology

# The Role of Personalization in Building Customer Trust in Chatbot Interactions for SMEs

**Mrs. Carmen-Nicola Ioniță**[1,†]

[1]*Academy for Games Media, Breda University of Applied Science ADSAI: Data Science AI*

This manuscript was compile on November 1, 2024

**Abstract**

The correlation examined in this study is between personalization and customer trust regarding the usage of chatbots within small to medium-sized enterprises (SMEs). "How does personalization influence customer trust in chatbots?" is the research question to be answered. In order to do that, a mixed method study that incorporated a quantitative survey of 180 respondents and in-depth semi-structured interviews with 5 respondents who have interacted with chatbots recently will be used.

The findings of the quantitative study show a significant and positive relationship between the elements of personalization and trust in chatbots. This relationship is rather strong as $r = 0.6564$ and $p < 4.5857e-23$. Thus it is very fundamental. The Pearson correlation analysis carried out allows for the rejection of the null hypothesis, which held that there is no effect or rather no statistically significant relationship between the level of personalization of chatbot interactions and customer trust in a chatbot.

To facilitate this measurement of each variable and its significance, composite scores were calculated for personalization and trust/acceptance from a number of questions on the survey. The quantitative results are reaffirmed by the qualitative insights, which support the conclusion that personalization influences customer trust in chatbots in the context of SMEs.

The results suggest that increased customer trust will be gained from the incorporation of personalization mechanisms in chatbot design, which is useful in improving customer satisfaction and therefore customer retention in SMEs.

**Keywords:** *Chatbots, Customer Trust, Personalization, SMEs, Customer Service Technology, AI-Human Interaction*

**Corresponding author:** Mrs. Carmen-Nicola Ioniță, Breda University of Applied Sciences, Department of Applied Data Science and AI, Breda, Netherlands.
*E-mail address:* 230632@buas.nl

## 1. Introduction

The popularity of chatbots has been on the rise in the recent past in the e-commerce sector, specifically in small and medium-sized businesses (SMEs) that aim to improve customer relations while saving time. As the use of such humanlike internet bots without a human touch increases, the discussion on the place of personalization in creating trust is recently becoming an important topic for scrutiny. This research seeks to fill this gap and understand how personalization affects customer trust in chatbot interactions in the SME sector.

The introduction of modern technologies and in this case, AI tend to make chatbots more effective in complex customer inquiries. However, an interesting issue is, how chatbots will be able to establish the relationship with the client and be trusted the same way that a human agent can. This is where personalization of the interactions, and transfer of information using one-on-one active mediums has been suggested as a way to build this trust.

Nevertheless, despite the benefits of personalization in reducing trust barriers, many questions on its applicability have been raised, particularly when it comes to the functionality of chatbots within SMEs. In other words, there is still limited empirical proof of the effectiveness of engaging through chatbots, especially when working in or targeting SMEs. Towards such ends, the research is motivated by the question: "How does personalization influence customer trust and acceptance in chatbots?".

This research will also provide congruent and conclusive evidence that personalization in chatbot interactions heightens trust and increases customer satisfaction levels as well as customer loyalty. This research also provides useful information for SMEs that deploy chatbots and yet they are still hesitant in regards to how this technology can help them boost trust levels among potential consumers. Also, the study is related to the ongoing research on human and AI interaction.

## 2. Literature review

The development and implementation of chatbots show significant progression in different domains and is still an area of active research. This review discusses the use of chatbots, recent advancements in the technology, incorporation in education, and factors that influence design.

### 2.1. Personalization in Chatbots

Personalization has emerged as a crucial factor in enhancing the effectiveness of chatbot interactions. In their work, Qian, Li, Zhong, *et al.* [4] published the PChatbot database that contains large numbers of query-response paired with information such as user and time. This dataset is important because it addresses the problem of insufficient data for training different Natural Language Generation dialogue systems, creating the possibility of personalized dialogue models that can learn implicit user personality from dialogue history. As an extension of this, Shumanov and Johnson [5] examined the issue of enhancing the chatbot interaction by matching the consumer with the machine personalities through language. Their research, conducted using chatbot record data from 57,000 seminars, showed that the consumer's personality can be profiled and that the chatbot can be reprogrammed to act like a character in the 'dialog' by using specific phrases. More importantly, it was observed that the enhancement of the interaction and sales outcomes was very effective where the personality match applied to the user was equal to the chatbot involved, particularly when in activities that involve social losses.

### 2.2. Educational Applications of Chatbots

Large numbers of people have turned to AI Chatbots for a guiding hand in teaching and learning. In an essay studying the use of chatbots for higher education class settings, Iftene and Vanderdonckt [2] proposed MOOCBuddy, an intelligent system for recommending MOOCs to every learner proper to his/her profile. Unlike traditional chatbots, this chatbot utilizes social media profiles as well as your feeds, among other things, to help you choose the most suitable MOOCs. From the very beginning of this article, particularly in the context of social media, artificial narrow intelligence (ANI) programs and such human-like interactions or user tasks did not seem as surprising. Because of these reasons, in their analysis, the researchers focused on AI chatbots and possible applications of these technologies in understanding “learning behaviors” (such as in self-regulated learning, SRL) and “instructional” goals.

Chang, Lin, Hajian, *et al.* [6] further explored the educational potential of AI chatbots by proposing design principles that support self-regulated learning. Their research advocates for incorporating three essential educational principles: goal setting (prompting), self-assessment and feedback, and personalization. They emphasize the importance of teaching prompting for developing students' self-regulated learning (SRL) skills, configuring reverse prompting in AI chatbots to guide students' SRL and monitor understanding, and developing data-driven mechanisms for AI chatbots to provide learning analytics.

### 2.3. Chatbot Design and Implementation

Designing effective chatbots requires careful attention, as many factors must be considered. In his study, Hefny, Bolock, Herbert, *et al.* [3] introduces a model for character-driven chatbots, emphasizing important features such as the user's emotions, motivation, and metacognitive beliefs, which all impact the quality of conversation. This research highlights the complexity of creating effective chatbot interactions that can adapt to diverse user characteristics. The conceptual framework proposed by Hefny, Bolock, Herbert, *et al.* [3] is not only about emotions and personalities, but it also considers other aspects of human nature that are processed in the context of various algorithms. Such an instance is appreciating that chatbot communication solutions would be insufficient if they primarily focus on feelings or matching with some unique personality characteristic: individuals as a whole must be appreciated.

## 3. Methodology

The study integrated the use of both quantitative and qualitative data collection methods to perceive the relationship better between chatbot customization and customer trust in the context of small to medium-sized enterprises (SMEs). A comprehensive questionnaire was created and distributed through Qualtrics, a popular web survey application. The reason for using Qualtrics is because it gives a diverse demographic of people which enhances the generalizability and credibility of the study. The main objective of the survey was to evaluate several factors that determine how customers interact with chatbots, such as the extent of personalization experienced by the participants, their trust levels as well as various other contextual considerations that influence the use of the chatbot. Thus, in the opinion of this research, the enumeration of these aspects will offer an opportunity for helpful information on how such necessities as personalization could potentially affect people's trust toward chatbots within SMEs, among others.

The central hypotheses for this study are as follows:

- $\mathbf{H_0}$: There is no correlation between the level of personalization in chatbot interactions and customer trust in chatbots within SMEs.

$$H_0 : \rho = 0$$

- $\mathbf{H_A}$: There is a positive correlation between the level of personalization in chatbot interactions and customer trust in chatbots within SMEs.

$$H_A : \rho > 0$$

Where $\rho$ represents the population correlation coefficient between personalization and trust scores. This approach allows for a statistical test of the relationship between personalization and trust, while also providing flexibility to explore other factors that may influence this relationship through qualitative methods.

### 3.1. Survey Design

The questionnaire that is used in this research project was designed to take all the necessary aspects into account concerning customers' experiences regarding chatbot personalization and how that influences trust and acceptance. The survey has different sections focusing on Demographics, Chatbot Usage Experience, Personalization in Chatbot Interactions, Trust in Chatbots, and General Attitudes Toward AI. This design enables researchers to explore the biographical data of respondents, as well as their experiences and levels of personalization and trust in chatbots. This type of survey could serve as a starting point for creating correlations between variables.

Demographics Section:

This part records client details, including gender, age, and country of origin. These factors are very important as they aid in determining whether there is a link between particular client characteristics and their perceptions of chatbots' ability to personalize and build trust.

Personalization in Chatbot Interactions Section:

This section was of interest to the study, focusing on various aspects of personalization in chatbots. The questions include the extent to which chatbots utilize profile data (Q31), adjust based on user input and preferences (Q32), adapt language and tone (Q33), recall previous conversations (Q34), and provide suggestions based on interests (Q35). With the purpose of evaluating the significance of personalization in chatbot interactions, the results from the five questions were combined and a new variable named “Personalization” was created.

Participants rated their trust in chatbots based on several factors, including transparency in decision-making (Q36), ease of navigation (Q38), the chatbot's ability to understand emotions (Q41), and its use of a relatable tone (Q42). The results from these questions were aggregated to create a *Trust_acceptance* variable, which was used to assess the outcome of the study. While many questions were designed to capture a broad understanding of customers' chatbot-related attitudes, the following composite variables were directly relevant to the research aim of investigating the relationship between personalization and trust in chatbots:

**Personalization:**

- Composite variable created from Q31–Q35. These questions represent aspects of personalization traits that could be considered in advanced chatbot systems and are expected to influence user experience.
- Example question: "To what extent does the chatbot utilizing data from your profile influence your trust and acceptance of the chatbot?" (Q31).
- Responses ranged from "Not at all" to "A great deal" on a Likert scale.

**Trust and Acceptance:**

- Composite variable created from Q36, Q38, Q41, and Q42. The questions were selected in line with the literature on trust in AI and human-computer interaction, which mentions concepts such as transparency, perceived competence, and relatability.
- Example question: "To what extent do you trust a chatbot that recognizes and responds to your emotions?" (Q41).
- Participants rated their trust on a scale from "Not at all" to "A great deal."

### 3.2. Data cleaning

The survey was distributed through Qualtrics. Data collection consisted of gathering responses from participants. The initial sample size was 179 complete responses. The data were cleaned to ensure that only valid entries were included in the analysis. After cleaning, the sample size consisted of 179 participants.

Data cleaning consisted of:

- Removing irrelevant columns such as language, location, ID, and distribution information, leaving only relevant data taken from the survey.
- Naming the first row of the dataset as "Q1", "Q2", etc., to maintain consistency and for ease of analysis.

### 3.3. Quantitative analysis

After the cleaning process, the dataset was prepared for analysis. Quantifying participants' experiences related to chatbot personalization and their trust and acceptance of chatbots was the objective of the study. To achieve this, the scores "Personalization" and "Trust_Acceptance" were created.

Determining these scores relied on the following procedures:

**Personalization Score:** The score was computed by averaging the responses related to the perception of personalization in the interaction with a chatbot, namely from Q31 to Q35 of the questionnaire. These questions were chosen because they represent different aspects of personalization: utilization of profile data(Q31), adjustments based on user input (Q32), language and tone adaptation (Q33), recall of previous conversations (Q34), and interest-based suggestions (Q35).

| | Q31 | Q32 | Q33 | Q34 | Q35 | Personalization |
|---|---|---|---|---|---|---|
| 2 | 3.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.2 |
| 3 | 2.0 | 2.0 | 2.0 | 3.0 | 2.0 | 2.2 |
| 4 | 4.0 | 4.0 | 3.0 | 4.0 | 4.0 | 3.8 |
| 5 | 5.0 | 4.0 | 4.0 | 5.0 | 2.0 | 4.0 |
| 6 | 3.0 | 3.0 | 4.0 | 4.0 | 2.0 | 3.2 |

**Figure 1.** Table displaying the columns Q31-35 and their averages in Personalization.

**Trust_Acceptance Score:** This is the mean of the responses related to the degree of trust and acceptance of the interaction obtained through survey questions such as Q36, Q38, Q41, and Q42. These questions were chosen because they highlight different nuances of trust in chatbots: transparency in decision-making (Q36), ease of navigation (Q38), the chatbot's ability to understand emotions (Q41), and its use of a relatable tone (Q42).

For both scores, responses given by participants were already on a 5-point Likert scale, and thus direct calculation was immediately possible without any mapping. Scaling was defined as:

- A great deal: 5 points
- A lot: 4 points
- A moderate amount: 3 points
- A little: 2 points
- Not at all: 1 point

Final scores for *Personalization* and *Trust_Acceptance* were computed for each participant by averaging the scores from their respective questions.

These values were computed to analyze the correlation between personalization and customers' trust in chatbots. These scores were used for further statistical analysis to answer the research questions and test the hypotheses of the current study.

### 3.4. Qualitative analysis

This research had the following plan: to conduct a series of semi-structured interviews focusing on core themes of personalization, emotional intelligence, transparency, security, and design within chatbot interactions. Each theme was crafted to elicit detailed responses about users' trust, convenience, and privacy expectations, with a specific focus on personalization. Questions for this theme—such as "How do you feel when a chatbot remembers your preferences or previous interactions?" and "Can you share a specific instance where a chatbot's personalized responses affected your experience positively or negatively?"—were designed to capture the direct impact of personalization on user trust and satisfaction. These questions allow participants to reflect on the benefits of personalization, such as improved efficiency, while also voicing any reservations about privacy and data retention. By addressing these elements, the research seeks to illuminate how personalization can foster user trust or, conversely, raise concerns, ultimately guiding SMEs in balancing customization with privacy considerations.[8]

Clients, after interactions with chatbots, tend to expect simple personal information to be something that the chatbot should be able to remember in the future. Everyone has their preferences regarding such data as whether it is okay for the chatbot to remember: "I don't want such sensitive data as bank details to be remembered by chatbots." This sentiment was echoed by others who preferred minimal data retention, stating, "It is better if the chatbot doesn't remember anything." Consequently, this phenomenon enhances the delicate relationship between user satisfaction and data privacy.

The implementation of personalization features presents an inherent contradiction between satisfying user convenience and respecting privacy preferences. Users with high privacy concerns may view excessive personalization negatively, potentially lowering their trust in the chatbot. As one participant observed, "I think it would be useful if it remembers more things... but some may be scared of this."

This insight underscores the need for a careful approach to personalization. SMEs should consider offering user controls over the level of personalization and be transparent about data usage to accommodate varying privacy preferences[7].

Our quantitative findings align with these qualitative insights. Questions related to profile data usage (Q31) and recall of previous conversations (Q34) indicated positive perceptions of memory functions. The high mean of Q34 (3.932) with a low standard deviation reflects a consensus that memory features enhance interaction efficiency.

The quantitative data is reinforced by qualitative responses praising advanced chatbots like ChatGPT for their ability to remember user preferences without repetitive input. As one user noted, "With ChatGPT, I don't have to constantly say, 'translate this in Romanian,' it already knows what I want," highlighting the value of customized responses for a more efficient experience. In conclusion, while personalization can significantly enhance user experience and interaction efficiency, its implementation must be carefully balanced with privacy considerations. SMEs should focus on providing personalized features that improve interaction without compromising user trust, particularly for those with high privacy concerns. Transparency in data usage and user control over personalization levels appear to be key factors in maintaining this balance[7].

## 4. Results

### 4.1. Quantitative results

The association between personalization in chatbot interaction and users' trust in them was analyzed using the Pearson correlation coefficient.

```python
def calculate_correlation(df):

    # Calculate correlation
    corr_coef, p_value = pearsonr(df['Personalization'], df['Trust_Acceptance'])

    # Display results
    print(f"Correlation Coefficient: {corr_coef:.4f}, P-value: {p_value:.4e}")
```

**Code 1.** Code to calculate the Pearson coefficient.

The Pearson correlation coefficient is a statistical measure used to assess the strength and direction of the linear relationship between two continuous variables. It ranges from -1 to +1, where -1 indicates a perfect negative linear relationship, +1 indicates a perfect positive linear relationship, and 0 indicates no linear relationship Diez, Barr, and Cetinkaya-Rundel [1]. The results are as follows:

Correlation Coefficient: 0.6564

p-value: 4.5857e-23

These results would seem to indicate a strong positive relationship between personalization level in the chatbot interaction and user trust or acceptance.

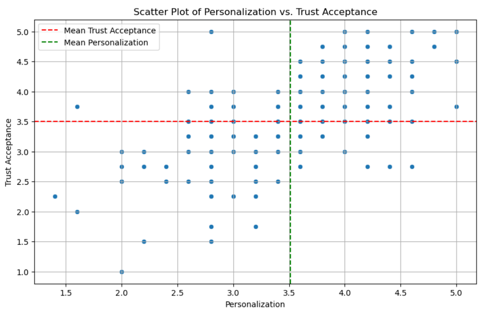


**Figure 2.** Scatter Plot of Personalization vs. Trust.

### 4.2. Trust/acceptance and Age

To investigate age-related trends in the relationship between trust/acceptance in interacting with chatbots, a follow-up analysis was conducted: Correlation Coefficient: -0.0029 This would be equivalent to a very low negative association of age with trust/acceptance.

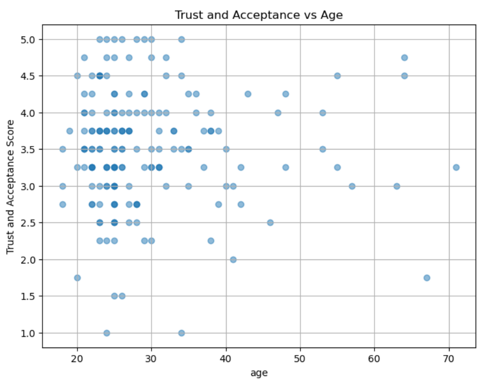


**Figure 3.** Scatter Plot of Trust vs. Age.

### 4.3. Personalization and Age

A related question concerns the relationship between age and personalization of chatbot interactions: Correlation Coefficient: -0.0363 This would mean an extremely weak relationship between age and personalization.

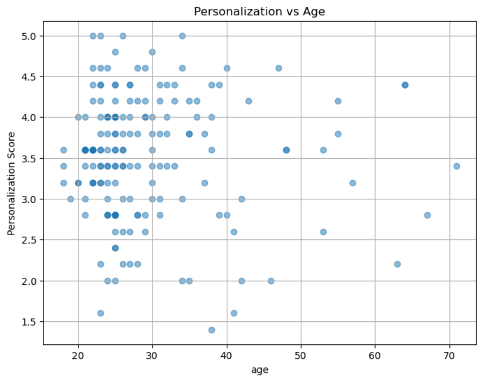


**Figure 4.** Scatter Plot of Personalization vs. Age.

### 4.4. Descriptive Statistics

| Question | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Q31 | 3.358 | 1.081 | 1 | 5 |
| Q32 | 3.386 | 0.979 | 1 | 5 |
| Q33 | 3.403 | 1.182 | 1 | 5 |
| Q34 | 3.932 | 0.983 | 1 | 5 |
| Q35 | 3.483 | 0.997 | 1 | 5 |

**Table 1.** Descriptive Statistics for Survey Questions.

Results from Question 31 (profile data usage) are that the general attitude of the respondents is quite positive, as can be viewed by the mean of 3.358. The very high standard deviation of 1.081 shows that many participants were dissatisfied with chatbots using data from their profiles.

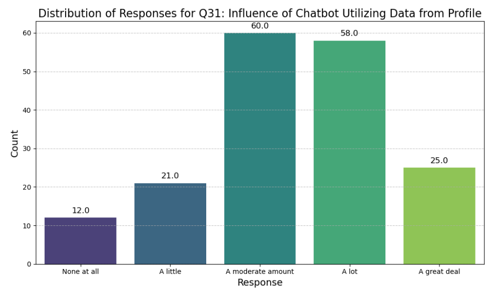


**Figure 5.** Bar chart Q31.

Q32 (adjustments by user input), has an average of 3.386, which shows that test subjects fairly and prospectively believe in the capability of chatbots to make changes based on what the users input. The standard deviation stands at 0.979, showing more consistency in their responses, although there is again considerable variation in user experience.

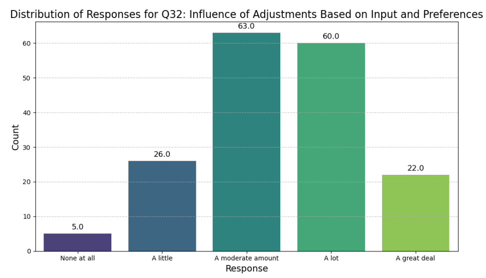


**Figure 6.** Bar chart Q32.

In contrast, the mean for Q33 (Use of Language and Tone) is 3.403, indicating that overall, users consider chatbots good in varying their languages and tones, though there is huge variation as represented by a standard deviation of 1.182.

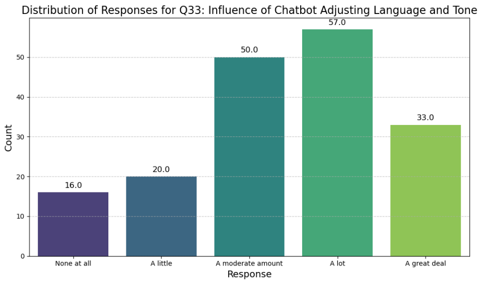


**Figure 7.** Bar chart Q33.

Q34 (recall of previous conversations): outstanding, the mean is high: 3.932, reflecting a high consensus about such a fact: chatbots remember past interactions effectively. A standard deviation of 0.983 shows a low value, further enhancing this positive perception, despite some users continuing to report some problems with active memory.

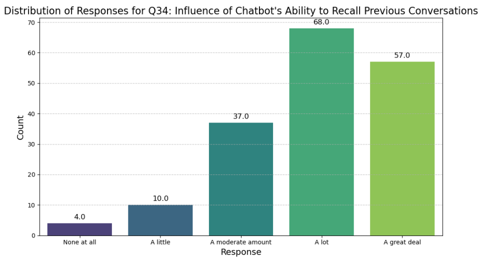


**Figure 8.** Bar chart Q34.

Eventually, Q35 shows that Interest-Based Suggestions rate on average 3.483 out of users' perception of added value in getting recommendations suitable for their interests. However, responses are not very positive. The standard deviation of 0.997 shows that participants are moderately unanimous, believing that some users consider such recommendations to be pertinent while others do not.

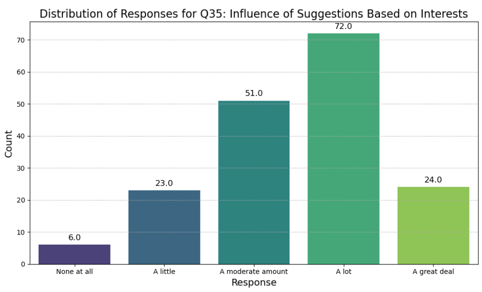


**Figure 9.** Bar chart Q35.

### 4.5. Qualitative results

Results have shown a good coherence between the quantitative and qualitative results about chatbot personalization and user trust. Quantitatively, questions about the usage of profile data, Q31, and remembering past conversations, Q34, had very positive feedback on these memory functions. Most impressively, Q34 reached a high mean of 3.932 with low variance, which indicates there is one shared belief: that memory will enhance the efficiency of interactions.

Qualitative and quantitative findings point in the same direction: personalization improves user experience and builds trust in chatbots by users, provided it addresses individual privacy expectations. This would inherently indicate alignment: careful implementation of memory features by SMEs necessarily has to go hand in hand with transparency in building processes of trust and taking care of privacy.

## 5. Discussion

This paper discusses the relation between personalization in interaction with chatbots and the level of trust in the system by users and considers how age may affect such relationships. The expected results will be of great importance for mapping this relationship in the context of SMEs.

### 5.1. Interpretation of Key Findings

The study was guided by the following hypotheses:

- **Null Hypothesis (H0):** There is no significant relationship between the level of personalization in chatbot interactions and customer trust in chatbots.
- **Alternative Hypothesis (H1):** There is a significant positive relationship between the level of personalization in chatbot interactions and customer trust in chatbots.

The strong positive correlation, $r = 0.6564$, $p < 0.001$ (clearly smaller than 0.05), between personalization and trust/acceptance gives clear reasons for rejecting the null hypothesis while proving the alternative hypothesis. This also agrees with general literature evidence that personalized experiences can increase user participation and gain trust in digital interaction courses Diez, Barr, and Cetinkaya-Rundel [1].

The rejection of the null hypothesis with the statistical significance of the relation between personalization and trust provides evidence that the personalization features must be embodied in chatbots deployed by SMEs. Profile information usage, reacting to user activity, and remembering past conversations, represented by Q31-Q35 features, tend to appear very strong in building trust.

### 5.2. Implications for Chatbot Design in SMEs

Considering this, the high level of associated trust would create significant incentives to include features of personalization within chatbots when using SME applications. Given the availability of profile information, the incorporation of user feedback, and remembering previously or even previously negotiated or decided things specifically, the questions Q31-Q35 assessed these-end.

### 5.3. Limitations and Potential Biases

One major drawback of the present study, however, is that the age distribution is very biased, with participants top-heavy in the 20-30 age bracket. This could well skew relational variables of personalization and trust/acceptance so that age-specific effects which might have appeared, had the sample been more diverse in terms of age, were obscured. More importantly, reliance on self-report measures of trust and adoption would invite response biases. One could not be guaranteed that the evaluations by the subjects of their trusting levels could match what they actually did or a long-term attitude towards chatbots.

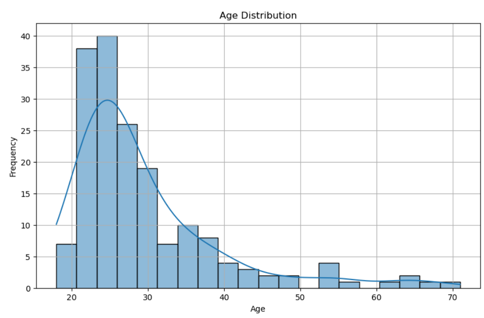


**Figure 10.** Age Distribution.

One of the most significant limitations of the present study is geographic bias, with most participants from South Africa. This concentrates perceptions that may distort personalization and trust due to variation in technology adoption and interaction preferences based on cultural or regional reasons. Subsequent research needs to have a more geographically diverse sample so that the findings here support those from a wide range of cultural contexts.

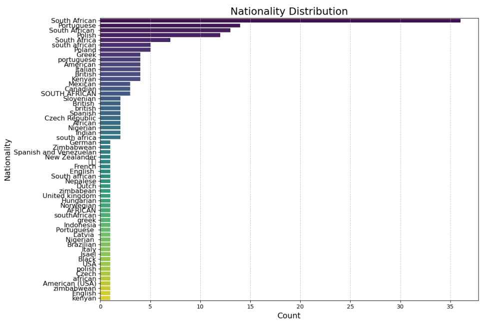


**Figure 11.** Nationality Distribution.

### 5.4. Future Research Directions

Future studies should, at the very least, attempt to sample across different age groups for an indication of the moderation effects of age on personalization and trust in chatbots. Longitudinal studies could also further address how trust in chatbots may evolve over time with continuous use and exposure to personalization. This may imply a few practical ramifications for chatbot developers or SME managers who will apply this AI, particularly features which produce much of the increase in personalization trust.

## 6. Conclusion

This research aimed to establish the connection between levels of personalization in chatbot interaction and customers' trust in chatbots within SMEs. Given the strong positive relationship between the levels of personalization in the chatbot interaction and customer trust, this is strongly supportive of the alternative hypothesis.

The analysis revealed a strong positive correlation $r = 0.6564$ and $p < 0.001$ between the dimensions of personalization and user trust/acceptance; thus, as chatbots become more personalized, users will tend to build more trust in such interactions. This evidences the need to embed effective personalized touches within chatbot design so that users can derive better satisfaction and build trust in interactions.

Importantly, the study explored these associations further, in respect of the role of age, and found no significant correlations. These weak negative correlations, -0.0363 for age with personalization and -0.0029 for trust/acceptance suggest that age is of little consequence in the variation of perceptions regarding chatbot personalization or trust. This goes to argue against several common assumptions about inter-generational differences in the use of technology. However, generalization is not likely to operate that strongly, considering some of the limitations this study has, biases toward a young subject pool, and inability to generalize across geographical regions. Further research should, therefore, consider more representative samples to understand the interaction between the various factors affecting such a relationship between personalization and trust.

This therefore means that this study brings out the importance of personalization in developing trust in the chatbot interactions at SMEs. By focusing on robust personalization capabilities, organizations can ensure improved user experiences and deeper user relationships with their clientele. With the pace at which developments are taking place around artificial intelligence, this is a dynamic of which companies would want to be aware when leveraging such technologies as chatbots in the corporate world. In-depth research on concrete personalization strategies and their effects among various user demographics offers considerable potential for optimizing benefits from AI-powered customer service interactions.

### 6.1. Recommendations

Based on the results of this study, SMEs should keep these recommendations when implementing chatbots:

1. Properly manage user data, and specific preferences: Build systems capable of processing and storing user preferences securely, making sure to handle data interactions.
2. Retain information from past dialogues: Add a conversation history feature to the system so that bots can refer to user interactions and conversations to facilitate in-context response capabilities.
3. Offering proactive recommendations: Employ MPI algorithms for user's behavioral data analysis and recommend suitable articles, businesses, or even topics of concern to the user.
4. Introduce an "Explain this" button that will allow users to receive detailed explanations about the chatbot's answers or recommendations. This feature will contribute to transparency, therefore to the customer's trust in chatbots.

## References

[1] D. M. Diez, C. D. Barr, and M. Cetinkaya-Rundel, *OpenIntro Statistics*. Boston, MA, USA: OpenIntro, 2012, vol. 4.

[2] A. Iftene and J. Vanderdonckt, "Moocbuddy: A chatbot for personalized learning with moocs", in *RoCHI–International Conference on Human-Computer Interaction*, 2016, p. 91.

[3] W. E. Hefny, A. E. Bolock, C. Herbert, and S. Abdennadher, "Towards a generic framework for character-based chatbots", in *Highlights in Practical Applications of Agents, Multi-Agent Systems, and Trust-worthiness. The PAAMS Collection: International Workshops of PAAMS 2020, L'Aquila, Italy, October 7–9, 2020, Proceedings 18*, Springer International Publishing, 2020, pp. 95–107.

[4] H. Qian, X. Li, H. Zhong, Y. Guo, Y. Ma, Y. Zhu, *et al.*, "Pchatbot: A large-scale dataset for personalized chatbot", in *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, ACM, Jul. 2021, pp. 2470–2477. DOI: 10.1145/3404835.3462933.

[5] M. Shumanov and L. Johnson, "Making conversations with chatbots more personalized", *Computers in Human Behavior*, vol. 117, p. 106 627, 2021. DOI: 10.1016/j.chb.2020.106627.

[6] D. H. Chang, M. P. C. Lin, S. Hajian, and Q. Q. Wang, "Educational design principles of using ai chatbot that supports self-regulated learning in education: Goal setting, feedback, and personalization", *Sustainability*, vol. 15, no. 17, p. 12 921, 2023. DOI: 10.3390/su151712921.

[7] OpenAI, *ChatGPT*, Accessed: 2024-11-01, 2024. [Online]. Available: https://openai.com/chatgpt.

[8] OpenAI, *Chatgpt [large language model]*, 2024. [Online]. Available: https://chatgpt.com.