

Customers' perspectives on trusting virtual conversational assistants

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Abstract

Anthropomorphism has been recognised as a factor contributing to trust of technology, particularly in fostering affective trust among users. Utilising Mayer et al.'s integrative model of trust the antecedents of trustworthiness influenced by anthropomorphism are explored. The research employs a qualitative and inductive methodology, utilising the critical incident technique. Data were collected through one-to-one semi-structured in-depth interviews with a purposive sample of 92 customers from the financial services sector in South Africa. Findings indicate an association between anthropomorphism and perceived benevolence. Additionally, some participants raised ethical concerns, suggesting that anthropomorphised agents may lead customers to mistakenly believe they are engaging with human representatives, especially when these agents introduce themselves using human names. This study is practically relevant as financial services institutions (FSIs) by informing the design of AI-driven customer engagement strategies that enhance trust and interaction through tailored chatbot elements, such as language style, avatars, and branding.

Keywords: Anthropomorphism, Trust, Artificial Intelligence, Human-AI interactions

Introduction

Trust in AI is crucial for the adoption and sustainable use of AI applications (Łapińska et al., 2021). Similarly, anthropomorphism, that is the humanising of AI applications, plays a crucial role in AI applications, facilitating user adoption of AI-empowered applications such as virtual conversational assistants and enhancing engagement, thus promoting user competence and understanding of AI-empowered technologies (Darling, 2015, 2016; Salles et al., 2020; Złotowski et al., 2014). Anthropomorphism manifests in various forms, including the inherent attribution of human characteristics such as intentionality and cognitive abilities and the encapsulation of will and emotion. Anthropomorphism may also encompass expressions like smiles or friendly greetings (Proudfoot, 2011). Anthropomorphism involves the attribution that AI systems can predict and comprehend information similarly to humans, reflecting the imitation of human cognitive processes, as exemplified by deep neural networks employed in virtual conversational assistants (VCAs) such as Siri (Salles et al., 2020).

Organisations within the South African Financial Services Industry FSI have actively adopted VCAs as part of their digital transformation initiatives (Jang et al., 2021). VCAs are empowered by generative AI to respond to user prompts in natural language (Dhake et al., 2024). VCAs are anthropomorphised through avatars (human or inanimate), human names (Fakhimi et al., 2023; Waytz et al., 2010).

However, there are ethical implications of anthropomorphism that raise significant concerns, particularly regarding its potential to influence user decision-making processes through the incorporation of anthropomorphic features (Hartzog, 2015; Salles et al., 2020). The use of anthropomorphism in artificial intelligence may also mislead users into believing that such systems

are able to engage with them at an emotional level (Salles et al., 2020). Moreover, there are privacy concerns associated with anthropomorphism, as users may be inclined to share personal information with AI applications in a manner of confiding in a friend, such disclosures often being utilised to benefit the organization rather than the individual (Salles et al., 2020). Despite these ethical concerns researchers have concluded that anthropomorphism in virtual AI agents results in the creation of affective trust (Gkinko & Elbanna, 2023; Glikson & Woolley, 2020). However, it remains to be explored how and which specific antecedents of trustworthiness are influenced by anthropomorphism.

The study is organised as follows: The next section discusses the literature review, outlining the research questions, followed by the methodology. Finally, the findings and a discussion of the findings are presented, and the conclusion includes recommendations for future research. The study contributes to the understanding of how participants perceive ABI trustworthiness antecedents when VCAs are anthropomorphised.

Literature Review

Trust as a psychological state

Trust, as a psychological state, is the “willingness [of the trustor] to be vulnerable in the face of uncertainty, predicated on a positive expectation regarding the intentions or behaviours of another [the trustee]” (Rousseau et al., 1998, p. 395). This notion of vulnerability involves accepting risk, grounded in the belief that the trustor will not experience harm (Mayer et al., 1995). It is crucial to note that while a trustor may demonstrate a readiness to be vulnerable, this does not necessarily imply a complete acceptance of risk; rather, the presence of perceived risk, as without perceived risk, trust is not needed (Rousseau et al., 1998). To facilitate the establishment of trust, it is imperative

to align several critical components, which encompass a willingness to embrace vulnerability, the cultivation of positive expectations from the trustor, and to the presence of perceived risk in uncertain situations (Castaldo et al., 2010; Colquitt et al., 2007; Wang et al., 2015).

Trustworthiness

When assessing a trustee's trustworthiness, the authors have summarised it to three antecedents which are, ability, which is the capability to fulfil the assigned tasks; benevolence, which involves acting sincerely and without hidden intentions to fulfil the requirements of the trustor; and integrity, meaning the trustor believes the trustee shares the same values, beliefs, and principles (Mayer et al., 1995). The ability, benevolence and integrity (ABI) trustworthiness factors are interconnected, and the absence of any one of them would diminish trust (Mayer et al., 1995). The foundational and most easily noticeable factor for establishing trust is ability (Castaldo et al., 2010). Ability is context-dependent; for example, an individual may excel in one domain while encountering challenges in another (Rousseau et al., 1998).

Benevolence is the expectation that the trustee will act sincerely (Colquitt et al., 2007) and serves as an example of a trustee who exceeds expectations without seeking reward (McAllister, 1995). The emotional connection that the trustor believes they have with the trustee is described as benevolence (Dietz & Den Hartog, 2006; Rousseau et al., 1998). Benevolence is the feeling of care, including empathy. Over time, the sense of benevolence develops and requires ongoing communication between the trustee and the trustor (Colquitt et al., 2007).

Integrity is a crucial factor in establishing trust (Mayer et al., 1995). Integrity pertains to an individual's character and involves adhering to laws, principles, cultural values, and moral tenets; it signifies acting honourably and justly (Dietz & Hartog, 2006).

Dimensions of trust: cognitive and affective trust

Interpersonal trust comprises cognitive and non-cognitive (affective) elements (Mayer et al., 1995). The assessment of trustworthiness, characterised by a positive expectation reflects cognitive trust, whereas a willingness to assume vulnerability signifies non-cognitive trust (Feitosa et al., 2020). Cognitive trust is established through rational evaluations by the trustor concerning the trustee's trustworthiness, ability, benevolence, and integrity (Lewicki et al., 2006). This dimension of trust necessitates collecting evidence regarding the trustee before deciding to trust (Lewicki et al., 2006). It is important to note, however, that there exists an overlap among the indicators of trustworthiness: benevolence is inherently affective, while integrity and ability are fundamentally cognitive in nature (Feitosa et al., 2020).

Affective trust is established through an emotional connection between the trustee and the trustor, which is fostered by consistent communication. This relationship is mutually advantageous, as it is characterised by genuine concern for each other's well-being (McAllister, 1995). Affective trust emerges when the trustor feels secure in their capacity to rely on the trustee. When assessing trustworthiness, the trustor experiences emotional security regarding the trustee based on previous interactions (McAllister, 1995). The differentiation between affective trust and the construct of trustworthiness lies in the nature of the trustor's feelings; for trust, the trustor possesses self-assurance regarding their vulnerability. Conversely, with trustworthiness, the trustor's feelings are

contingent upon the trustee's actions, which may be influenced by historical behaviours (McKnight et al., 1998). Furthermore, the presence of emotional bonds may become evident when trust is compromised; when a trustor experiences feelings of anger or betrayal, it serves as an indication that a significant emotional connection has been formed (Lewicki et al., 2006).

Virtual conversational assistants

Virtual conversational assistants (VCAs), also referred to as virtual customer assistants, known colloquially as chatbots, are computer programmes that replicate human speech, text, gestures, and (sometimes) facial expressions to simulate human discussions (Laranjo et al., 2018). Examples of virtual conversational assistants are Amazon's Alexa and Apple's Siri. The use of virtual conversational assistants in service environments is rapidly expanding across the globe in various industries, including banking (Lim et al., 2022). Financial services have three main types of VCAs: information, transactional and advisory. Information VCAs assist customers with basic repetitive questions; an example is providing customers with an explanation of financial terms in financial products they are interested in, whilst other information VCAs send reminders for payment for credit (Iovine et al., 2023). Transactional VCAs perform transactions for customers by using text or voice prompts in natural language. These would include making payments and investing in shares(stock) (Iovine et al., 2023). Advisory VCAs provide advisory services on financial products; this includes recommender systems that can recommend a suitable credit card for the customer's financial needs (Iovine et al., 2023).

VCAs fall under the category of narrow artificial intelligence, which means they are intended to handle specific tasks rather than exhibit general human-like intelligence. More sophisticated VCAs use self-learning algorithms to facilitate more effective interactions with humans. They depend on computational AI methods, such as deep learning and neural networks, to manage intricate

conversations. This functionality is enhanced by Natural Language Processing (NLP). The area of AI that allows programs to independently generate responses is referred to as generative AI (Marimon et al., 2025). Examples of such generative AI are ChatGPT and Deep Seek. Virtual conversational assistants are embodied in many forms. Virtual conversational assistants are embodied in many forms and, as such, can converse through voice or text or be embodied as an avatar (Lim et al., 2022). AI applications with anthropomorphic features significantly impact how humans engage with VCAs (Lalot & Bertram, 2024).

Anthropomorphism as a factor of trust in virtual conversational assistants

Anthropomorphism is the assignment of uniquely human emotions, cognitive states, and behaviours to non-human entities (Airenti, 2015; Epley et al., 2007; Salles et al., 2020). It highlights primarily the human psychological process of interpreting and making sense of uncertainty within their environment rather than focusing only on the characteristics of non-human objects (Salles et al., 2020). Anthropomorphism refers to a cognitive process characterised by the attribution of human traits, emotions, or intentions to non-human entities. This phenomenon is driven by two essential motivational needs that are fundamental to human psychology, namely: the necessity for individuals to experience a sense of competence and the fundamental human need for social connection (Epley et al., 2007; Salles et al., 2020; Waytz et al., 2010).

Anthropomorphism extends beyond the simple attribution of mental states; it also involves the assignment of emotional states and behavioural traits to inanimate objects (Epley et al., 2007). This phenomenon highlights the importance of the human perspective in understanding the reciprocal emotional dynamics inherent in anthropomorphic interactions. The emotional responses linked to anthropomorphism arise from human cognitive processing, allowing individuals to recognise their emotional reactions toward the anthropomorphised entities and not the other way around, where

the human thinks that the anthropomorphised entity has an emotional connection with the human. For example, one might develop a personal connection with an AI application rather than perceiving the AI as establishing a personal connection with the individual (Salles et al., 2020).

Trust occurs when risk is prevalent (Mayer et al., 1995), and anthropomorphism also occurs in conditions of uncertainty (Salles et al., 2020). Anthropomorphism requires the same conditions as trust, which is perceived risk in uncertainty. There have been contradictory views on whether anthropomorphism results in trust when the object of trust is AI. Anthropomorphism influences user engagement of virtual assistants. Anthropomorphism does not influence trust (Lalot & Bertram, 2024). Whereas other authors are of the view that anthropomorphism causes user trust for AI empowered applications (Gkinko & Elbanna, 2023; Glikson & Woolley, 2020).

Further, both trust and anthropomorphism are ascribed to a psychological process (Epley et al., 2007; Mayer et al., 1995). A unidirectional analysis from the perspective of the human is emphasised (Salles et al., 2020; Mayer et al., 1995). For trust, it is the human trustor who assesses the trustworthiness of the trustee without the trustee having to do the same for the trustor (Mayer et al., 1995). Similarly, anthropomorphism is from the perspective of the human towards the object, an assessment of an emotional connection needs to be from the human and not applied to the inanimate object (Salles et al., 2020). Some scholars have identified that anthropomorphism in virtual AI agents results to the creation of affective trust (Fakhimi et al., 2023; Gkinko & Elbanna, 2023; Glikson & Woolley, 2020). However, very little is found in the literature on the influence of anthropomorphism on cognitive trust, and literature is scant on which trustworthiness antecedents' anthropomorphism addresses leading to the following research questions:

1. To what extent and how do anthropomorphic features affect cognitive trust in VCAs?

2. To what extent and how do anthropomorphic features affect the trustor's perception of trustworthiness antecedents?

When assessing the trustworthiness of a trustee, the trustor considers three key attributes: competence, which reflects the trustee's capability to fulfil assigned tasks successfully; benevolence, which signifies their intention to act in good faith; and integrity, which denotes the alignment of the trustee's values, beliefs, and principles with those of the trustor (Mayer et al., 1995) aspect of the chatbot's perceived ability. AI is anthropomorphised in its ability to have a presence, show emotions, connect with people, emulate human connection and communicate initiatives to serve and influence trust in the AI application (Troshani et al., 2020). A personalised chatbot was perceived to be competent in an experiment conducted with 1001 participants as opposed to an impersonalised chatbot (Lalot & Bertram, 2024). Customers perceive anthropomorphising for ability based on how the AI application speaks or texts with the user (Troshani et al., 2020). AI applications are humanised to understand the nuances in the language from human interaction and are perceived as competent in addressing user inquiries (Troshani et al., 2020). Ability takes precedent in assessing trustworthiness in AI applications, where AI applications lack ability, anthropomorphic features become irrelevant (Lalot & Bertram, 2024).

2.1 To what extent and how do anthropomorphic features affect the trustor's perception of the ability of the VCA?

Benevolence is the feeling of care, including empathy. Customers tend to trust AI programmes that reflect empathy through language or speech (Hui et al., 2023). Anthropomorphised features in communication skills, such as responsiveness, attention, and affective expressiveness, provide the perception that the AI is benevolent (Troshani et al., 2020). Users focus on AI technology because of anthropomorphic elements deployed in AI systems, making them view it as benevolent (Lalot & Bertram, 2024). Users recognise that AI operates without independent intentions yet

anthropomorphic attributes generate benevolence perceptions, making them ignore how developers manipulate the system's actions (Lalot & Bertram, 2024). The growing psychological influence between users and AI requires developers to become the central focus because they shape all ethical attributes, functional properties, and societal impacts of AI systems. However, users are aware that AI lacks emotions, and empirical findings report contradictory results on whether these anthropomorphic features assist or deter customers from the perception that AI can be benevolent (Troshani et al., 2020).

2.2 To what extent and how do anthropomorphic features affect the trustor's perception of the benevolence of the VCA?

Research findings indicate that integrity is another crucial factor influencing trustworthiness, which entails believing that AI upholds the trustor's principles. Customers trust a company's integrity and as a result the brand, when satisfactory service is offered (Brodie et al., 2011), including services offered by AI applications (Troshani et al., 2020). AI applications appear to convey a sense of integrity by incorporating anthropomorphic features in communicating the level of integrity they may pose to users, users might be more likely to trust the AI, as they may perceive it to possess intention and, thus, integrity (Lalot & Bertram, 2024). However, the alignment of values and key principles with anthropomorphised AI applications is difficult to assess and achieve.

2.3 To what extent and how do anthropomorphic features affect the trustor's perception of the integrity of the VCA?

Methodology

This qualitative study investigates customer experiences and the significance of trust in interactions with virtual conversational assistants. Utilising an inductive approach, we aim to develop a theoretical framework that enhances existing interpersonal trust theories, particularly

the integrative model of organisational trust. Despite the robustness of these theories, their application to AI-based systems remains underexplored (Gkinko & Elbanna, 2023; Lalot & Bertram, 2024). By adopting an inductive methodology, our research contributes to the extension of interpersonal trust theories in the context of AI. Furthermore, the qualitative design facilitates a comprehensive understanding of the complexities surrounding human trust (Creswell, 2013).

Critical Incident Technique (CIT)

A critical incident technique research design was utilised to explore the psychological states of human trustors in reaching trusting decisions. CIT assisted in investigating critical events, by unpacking each participant's cognitive and affective psychological states (Seno et al., 2018). An event was identified as critical if it contributed to their psychological state in making a trust decision. CIT provided an understanding participants' psychological processes by extracting detailed explanations from the interviewees by referring to a particular critical incident, the results obtained from using the method assisted in the development of psychological theory (Flanagan, 1954).

In prior studies Critical Incident Technique (CIT) was utilised empirically to examine how trust factors are manifested in instances where intelligence professionals either gain or lose trust in AI (Dorton & Harper, 2022). The findings of the study indicated that using CIT provided insight into trust dimensions. Participants were interviewed by asking open-ended questions about a critical incident they experienced in using VCAs that had an impact on their trust decision (Abgeller et al., 2024) These incidents included situations that led to an increase in trust towards a VCA application. This captured the multifaceted and emotional aspects of trust while minimising the impact of recall

bias (Abgeller et al., 2024). The final step was the participant's reflection on the impact of the trust decision.

Upon receiving ethical approval, the principal researcher conducted comprehensive semi-structured interviews employing the Critical Incident Technique (Flanagan, 1954). This approach resulted in participants sharing significant incidents (Sloan & Oliver, 2013), which related to anthropomorphism and trust dynamics during their interactions with a virtual conversational assistant within the financial services sector. The participant's responses offered valuable insights into the mechanisms through which customers establish trust when engaging with an AI-driven application. Primarily the effects of anthropomorphic features in the assessment of trust and, secondarily, the participant's assessment of the trustworthiness of the VCA based on the anthropomorphic features. This approach explored trust's emotional and subtle aspects while mitigating recall bias by emphasising detailed descriptions of trust-related experiences. Following Flanagan's guidance on maintaining a flexible interview structure enabled the discovery of previously unrecognised nuances, thereby enhancing the comprehension of trust dynamics (Abgeller et al., 2024). Participants willingly shared their experiences, thereby facilitating a comprehensive examination of their perceptions of trust. During the interviews, they recounted specific incidents related to trust while researchers systematically analysed and interpreted these narratives. This methodological approach enriched the study's understanding of the dynamics of trust (Abgeller et al., 2024). The research was cross-sectional as the objective was to understand the phenomenon at a particular point in time (Saunders et al., 2023).

Population

In South Africa, the prevalence of bank account ownership among individuals aged 16 and older stands at 81%. However, this figure masks significant disparities within the population, particularly among the black demographic. The availability of social grants plays a crucial role in facilitating access to banking services; excluding recipients of social grants from the analysis reveals that the percentage of bank account holders among this group drops to just 20% (FCSA, 2023). The integration of social grant recipients into financial service inclusion metrics aligns the customer demographics of financial institutions more closely with the broader South African population. For instance, the largest bank in the country, as measured by the number of customers, boasts 19 million clients, the majority of whom are low-income earners. This highlights the critical intersection between social assistance and financial access in promoting economic participation among marginalised communities (Statista, 2022). Although there are disparities in financial access and financial inclusion, the FSI customer population is gradually approximating the South African population regarding racial distribution.

In South Africa, the legacy of apartheid continues to contribute to racial division, so it's important to elicit responses from all race groups. The Black African population group represents the largest segment of the South African population, comprising 81.4%. This is followed by Mixed Race/ Bi-racial at 8.2%, Caucasian/Whites at 7.3%, and Indians/Asians at 2.7% (*Key Statistics 2022*. 2024).

The population selected were customers of South African Financial Services Industry (FSI) organisations who have used VCAs as these customers would have had direct experience of VCAs as a result of the South African FSI adopting AI technology. VCAs converse in English; the population was further defined as English-speaking customers. Although FSI organisations have products for all age groups, including minors, the population excluded minors as they are not

legally emancipated, requiring the consent of a guardian adult; therefore, the study only considered customers above 18 years.

Sampling Technique

A purposive sampling technique was utilised (Etikan, 2016). To promote efficient chatbot utilisation and a customer-centric environment, financial services organisations need to consider the complex nature of consumer variety when conducting research (Srivastava et al., 2024). In applying the maximum variation purposive sampling technique, customer variation was considered to identify important factors in developing trust in chatbots. The South African population and dynamics were utilised as a target for selecting participants. As the customer base of FSI is heterogeneous, a maximum variation purposive sampling technique was used to capture the variation of participant responses (Ames et al., 2019). The primary characteristic for this study was to assess the trustor's knowledge of a chatbot. A trustor's knowledge of AI influenced the trust decision. The trustor's trust decision is influenced by age, gender and knowledge about the purpose and function of the technology (Łapińska et al., 2021). The customer's competence in understanding the function and objective of the AI included the customer's qualification, training, or work experience with similar AI tools (Łapińska et al., 2021). Factors identified were age, gender, knowledge of AI/chatbots (Łapińska et al., 2021) and race.

The sample selection criteria were based on whether individuals were customers within the financial services industry who had utilised a chatbot. Given the diversity of customers in the financial services sector, which encompasses variations in age, gender, and familiarity with artificial intelligence, these criteria were employed to ensure consistency with the demographic characteristics of the South African population.

Sample size

The population is heterogeneous as South Africa has a diverse population with different education levels, races, ages, cultures and ethnicities, which influences how participants develop trusting decisions. These heterogeneous views needed to be widely captured. For heterogeneous populations, a sample size typically ranges from 12 to 60 participants, larger sample sizes are permissible where participants are accessible and technology enables access to participants (Adler & Adler, 2012). A previous study on trust using the Critical Incident Technique (CIT) employed a sample of 50 participants (Abgeller et al., 2024). A sample of 92 participants was utilised for this study as referrals from participants increased, and the technology-enabled convenient interviews through the Teams and Zoom platforms.

Financial services industry customers were accessible; participants were selected from the researcher's network. Expanding our research through participant referrals was used to achieve a sample size of 92. Seven of the participants were experts in AI, AI developers, financial advisory, customer experience managers, or product managers, and 85 participants were customers. To ensure anonymity, participants' responses were coded; a prefix of “C” represents customer, and “E” represents expert. To ensure anonymity the participants are labelled according to race, age, gender and occupation. For a detailed description of the participants, refer to Appendix A.

Qualitative Data Analysis

A thematic analysis was utilised for the analysis of qualitative data in this study as it can accommodate large sample sizes and heterogeneous samples (Clarke & Braun, 2016). Data was

analysed inductively by creating codes from transcribed audio recordings (Braun & Clarke, 2006). We applied reflexive thematic analysis for data analysis (Braun et al., 2022). The primary author began with familiarisation, followed by generating initial codes, developing potential themes, reviewing and refining themes, defining and naming them, and finally producing the findings. Through this iterative and flexible method, we ensured that themes were meaningfully developed based on the researcher's interpretative insights (Byrne, 2021). Through the coding and analysis, coherent patterns were identified in the codes. The codes were then compared and grouped by similarity, and similar groups of codes were then grouped into themes. The transcript extracts allocated to the codes were always checked for accuracy in maintaining the original meaning. Once the themes were coherent, it was time to describe and name each theme accordingly. From the mapping two overarching themes emerged, which were the effect of anthropomorphic features on the dimensions of trust being cognitive and affective trust. The analysis was then focused on cognitive trust as we know through literature that anthropomorphic features in AI application result to affective trust (Fakhimi et al., 2023; Gkinko & Elbanna, 2023; Glikson & Woolley, 2020). The other overarching theme that emerged was the effect of anthropomorphism on trustworthiness antecedents which were insights on how the anthropomorphic features were assessed by participants to build trust. The thematic map is represented in Figure 1 below.

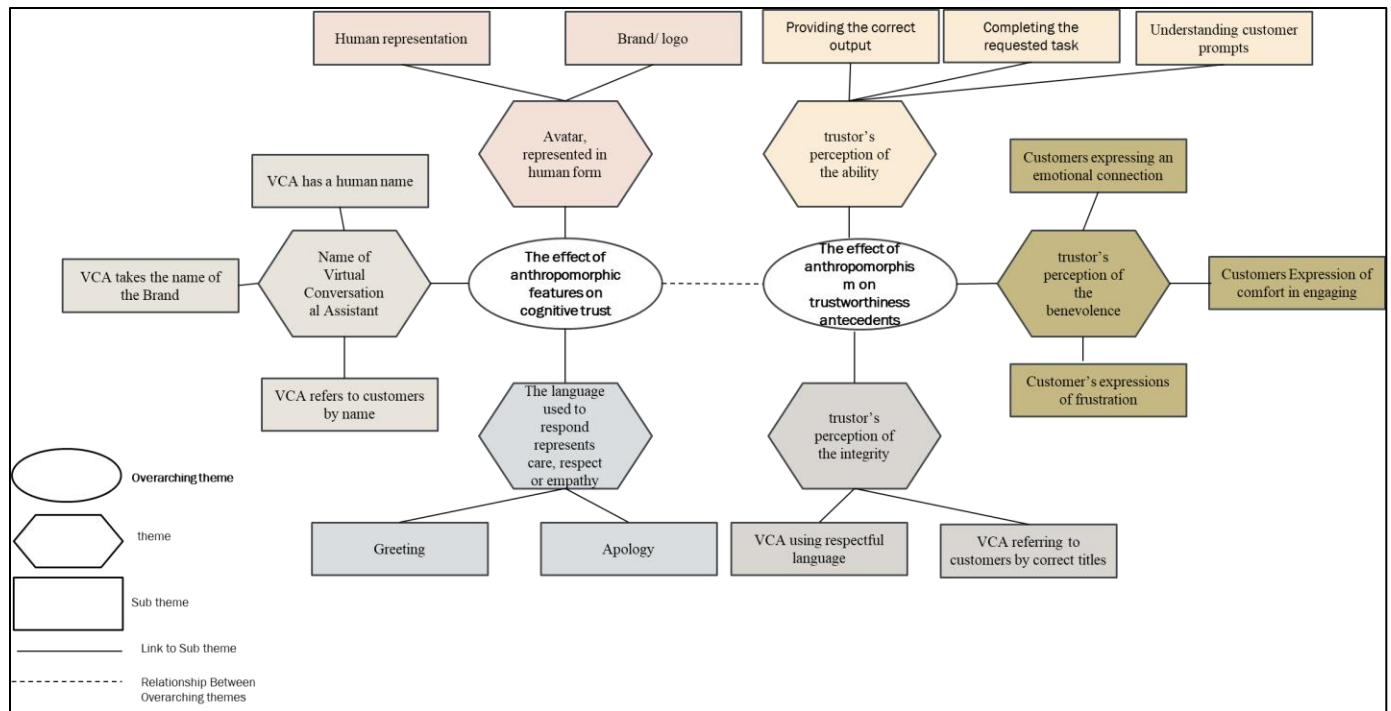


Figure 1: Thematic Map (Researcher's compilation)

Findings

This section introduces our findings into the role of anthropomorphic features in shaping the perceived trustworthiness of virtual customer assistants (VCAs) within South African financial service institutions. The analyses indicated two overarching themes presented in the section. The themes related to the overarching theme being the effect of anthropomorphic features on cognitive trust, were name of the virtual assistant, the avatar in human form for the virtual assistant, the language it uses to respond to customers. The themes related to the overarching theme being the effect of anthropomorphism on the trustworthiness antecedents was how the trustor perceived the ability, benevolence and integrity of the VCA based on the anthropomorphic features.

The effect of anthropomorphic features on cognitive trust in VCAs

Cognitive trust arises from gathering evidence about the trustee's trustworthiness (Feitosa et al., 2020). An expert in customer experience at a bank indicated that the anthropomorphic features of VCAs are designed to represent the brand. This participant has in depth knowledge about the bank they have been working for more than 10 years, although they did not have technical knowledge of AI, they were involved in the design of VCA to ensure customer satisfaction and alignment with the bank's brand. They further explained the importance of the name for the VCA. Thus, indicating that the name of the VCA was selected to represent a trusted financial advisor and intentionally selected to be a non-binary name, neither male nor female. Further, the language that the VCA used was also precisely selected to be professional but not too formal to be relatable to the current customer base.

"So, it always has to appear as a money expert who does good. Firstly, the name is Lotus. It... doesn't have a male or female stance, but it must sound knowledgeable because you're a money expert who does good – but caring" (E28)

A customer working for the same bank, who also has knowledge about the bank and has been working for the bank for more than 5 years, indicated that the VCA named "Lotus" was relatable, but the customer had reservations about the VCA, indicating that it is not a level at which it can replace human interaction. However, providing a name to the VCA provides a differentiator as to which VCA you are engaging with.

"Yeah, putting a name to something always creates a certain relationship... I think it's better to have a name. Then it's easier to differentiate, okay, this one does this, this one does that" (C6)

Most customers indicated that it did not matter whether the VCA had a human name or a human avatar as a virtual representation; rather it was the competency in understanding their request

mattered. Many customers indicated that VCAs greet and then direct the customer to a list of possible tasks in which they can assist, and in most instances, their request is not included in the list; therefore, they need to request for a human agent. Customer 3, a Senior Actuarial Analyst in the insurance industry and a frequent user of Bellflower Bank's VCA, compared the language used by VCAs from Bellflower Bank and Clovepink Medical Insurance. She expected a friendly tone from the medical insurance VCA, whereas her expectation for the bank's VCA was a more professional communication style.

"I don't know. I don't know why for this specific one (Clovepink medical insurance) I want it to be a bit more friendly, because in the Bellflower Bank instance I don't know if it was money matters, but I understood the professionalism that we keep between myself and the chatbot. But for some reason with this one, I don't know hey, I actually don't know why I expect it to be more warm (laughs)." (C3)

The initial thoughts by customers when interacting with an anthropomorphised VCA is that they are interacting with a person, however as the discussion progresses, they realise that they are speaking to a machine and the cognitive process of assessing trust from the perspective of a programme and start to accommodate the programmes limitation in coming to a trust decision. Customer 10, Head of Data Management and Governance at a bank, requested to be interviewed as a customer rather than an expert. Despite this, their industry knowledge and IT qualification led to in-depth insights on VCA adoption in financial services. In assessing cognitive trust through anthropomorphic features, Customer 10 noted that while these features initially make customers feel they are interacting with humans, they eventually realise that it's a VCA their interacting with.

"At first interaction you are thinking, oh, there must be a person behind, ... this interaction. But as you carry on then you actually discover, but wait a minute, these sound like scripted questions. If you ask a question where it's stuck, you know, it will respond with the same set of answers that it had responded with, you know, previously. And I think perhaps for me, because I'm a bit privileged because I understand programming, then you'd

immediately pick up to say, okay, wait a minute, I'm actually not speaking to an individual here, but I'm speaking to another programme." (C10)

The effect of anthropomorphic features on the trustor's perception of the ability of the VCA

Ability refers to the VCAs competence in fulfilling a task, however ability needs to be considered within the context of the trustee's capability. Anthropomorphising VCAs gives the impression that they are competent and can perform the work as efficiently as humans or even better. The objective of FSI organisations is to reduce human-human interaction traffic from call or service centres. Therefore, giving the chatbot human traits such as a name and language gives customers the perception that it is efficient. A customer of a bank who is also an employee of the same bank indicated that giving the VCA human traits gives the customer the perception that it is competent.

"This is there to answer our questions, and obviously, they are also there to reduce the amount of human interaction in a certain way. So, the purpose is to reduce error and to be more efficient. So, it takes that form of a human form ...so it's easy to relate with it...then we can also go back to it. It is mainly to make our lives easier, better and more efficient so we can focus on things that we consider to be more important to us" (C6)

Participants were of the view that anthropomorphism provides the impression that the VCA is competent only at the initial stage of interaction. At the initial stages there is a perception that the VCA would have a similar intellectual capacity as a human. Some participants expressed a belief that chatbots, despite being inanimate objects, could still be perceived as having agency. This perception was influenced by the chatbot's ability to respond intelligently and adapt to the conversation, leading some to refer to them as "they" rather than "it". However, the perception of human agency is short-lived as the interaction continues. When participants start interacting with the VCA, they realise that it is not as competent as they had initially perceived it to be.

"But as you continue interacting, you can see in the response. You can see the cold response [slight laugh]. There's no, you know, human words or words of affirmation or words of understanding your situation. It is just straight to the point and at time the

interaction was obviously with a scripted bot. I know probably by this time around, nowadays, you know, they try and programme them so that they can at least attach a bit of emotion to them. But it was so [slight pause] cut to the point.” (C10)

VCAs lack the emotional capability affected by the way participants assess the ability trustworthiness of the VCAs. Although most participants were aware of this limitation, due to the VCAs anthropomorphic features, there was an expectation for the VCA to be empathetic and understand enquiries beyond its programming. Participants reported selecting the option to interact with a human agent to complete the task when the VCA lacked the ability to understand the query. Anthropomorphism creates an expectation of competence to understand at a human level, and when the VCA does not meet the required expectations, participants report feeling frustrated.

“So sometimes, I don't know if it's language barrier or what, but it feels like the app doesn't understand what you're saying, or it's giving generic answers. So only then would I actually follow up with a call, because they actually call me.” (C3)

The effect of anthropomorphic features on the trustor's perception of the benevolence of the VCA

Benevolence is assessed through evidence of the trustee's goodwill and the fact that they will not cause harm to the trustor. Benevolence is the perception of a positive orientation of the trustee toward the trustor (Mayer et al., 1995. p719). Benevolence is further established through emotional bonds. Literature has established that anthropomorphism creates emotional and social connections leading to affective trust (Fakhimi et al., 2023; Gkinko & Elbanna, 2023; Glikson & Woolley, 2020). However, it is not clear whether anthropomorphic features are perceived by customers as the VCA having benevolence. Many participants noted that giving chatbots human names or characteristics made their interactions feel more personal and relatable. For instance, one respondent mentioned that having a chatbot named "Red" provided comfort and made the interaction feel less robotic, enhancing their expectation of human-like interaction. Participants

often felt a stronger connection to chatbots that appeared more human-like. Customer 6 indicated that when the VCA greets you it makes it relatable, it built a level of connection that felt more emotional than clinical, suggesting that the anthropomorphism of chatbots can foster trust

“This thing it’s an answering machine, it says ‘hello’...I’m so-and-so, and they make it so relatable that I can tell it’s a black person. It’s not that foreign language that you can easily tell that, no, this is not a person. So now they use people’s voices that you can... you feel like it’s a human being” (C6)

Customer 24, a financial manager at a state-owned company who neither has expert knowledge about the financial service industry nor technology, indicated that when the chatbot has a human name, and uses language that is used by humans. The interaction between the chatbot and the customer is so comfortable to an extent that the customer discloses personal information.

““I mean, you become comfortable to (pause), to ask your questions or to request the information that you're requesting, (pause), you trust it in a way that you are able to disclose your security question, your security answers because you know that it is a secure chatbot...I mean, yeah, you develop a level of trust. You, you're not saying, okay, this is a robot. I cannot trust the machine. No. And with my intention with the chatbot, I never had that thing that I'm interacting with the machine.” (C24)

The effect of anthropomorphic features on the trustor's perception of the integrity of the VCA

Integrity relates to “the trustee adheres to a set of principles that the trustor finds acceptable” (Mayer et al., 1995). Values are intrinsic and would not necessarily be assessed through external interpersonal interaction features. However, it was worth investigating whether anthropomorphic features in VCA are perceived as contributing to integrity. Customer 35, a software developer at an insurance company, who has entry level working knowledge of the financial services industry as they have only been working for a few years and also has an IT degree. Indicated that values are assessed in the language VCAs use to address customers. For example, referring customers by their title provides a perception of respect. The customer further elaborated that the VCA aligned

to their values of “treating people the way you want to be treated”. The VCA achieved this by the use of proper grammar, avoiding capital letters, exclamation or bold letters, which would have been interpreted as shouting.

“It can, it can align to your values, because it needs to address you respectfully, ... Like in my instance it was just saying ‘Hello Name of Participant’. In some other instances, people like to be called ‘Doctor’, Mr, Mrs, and then there are now people who are gender neutral. And then for me those are not as important, whatever you (pause), if you call me by my name then I am still good with it” (C35)

“I want to accommodate other people in most instances... it did align with my (pause) my values because it didn’t type in bold capital letters, and then also the exclamation marks it didn’t use, like ‘How are you!’ it sounds like someone is shouting at you or rushing or something. Yeah. So, it did align to my values.” (C35)

Discussion

This study reveals that anthropomorphism plays a crucial role in customer engagement with chatbots. However, there are conflicting perspectives on whether customers of financial services institutions (FSIs) consider anthropomorphism an essential factor in shaping their perception of trustworthiness antecedents.

To what extent and how do anthropomorphic features affect the trustor's perception of the ability of the VCA?

Providing anthropomorphic features on a VCA gives customers the initial impression that the AI application is competent and can understand cognitively and affectively the customers’ requirements. However, this perception is lost when the VCA fails to understand the customers’ requirements. The findings are consistent with (Lalot & Bertram, 2024), in that ability is takes precedent over anthropomorphic features which provides the perception of competence. The study is also consistent with the findings of (Troshani et al., 2020) in that customers assess the ability

through anthropomorphised language in speech and text. The perception of ability is elevated when the VCA can understand the customer. The new findings extending current literature is that the anthropomorphic features intended to make the AI application competent are irrelevant over time, specifically when the AI application is not perceived to be competent, that is, when it does not understand the customer's requirements.

To what extent and how do anthropomorphic features affect the trustor's perception of the benevolence of the VCA?

The findings indicated that customers perceived anthropomorphic features in the VCA to stimulate emotions and the belief that the VCAs and the organisation care about them. These findings are consistent with (Troshani et al., 2020). However, the findings diverge from those of (Lalot & Bertram, 2024), who indicate that for anthropomorphised AI, participants consider the benevolence of the AI application rather than the developers behind the VCA. This is contrary to the findings in study where participants indicated that the organisation's and the developers' benevolence is still considered when assessing trustworthiness.

To what extent and how do anthropomorphic features affect the trustor's perception of the integrity of the VCA?

Participants indicated that the VCA aligned with their principles when they used respectful language and referred to them by the correct title. These findings are aligned with (Troshani et al., 2020) in the use of language to anthropomorphise integrity. However, the VCA were not advanced to self-report the level of integrity they possess, there was therefore no opportunity to assess self-reporting VCAs with the SA financial services industry as per the findings of (Lalot & Bertram, 2024).

Conclusion

This study explored the role of anthropomorphic features in shaping customers' perceptions of trustworthiness in virtual customer assistants (VCAs) within South African financial services institutions (FSIs). The findings highlight the significance of specific anthropomorphic features in fostering trust, with the usage of language emerging as a particularly influential factor. Additionally, the ability of VCAs to convey empathetic behaviour, such as offering verbal apologies following service limitations, further contributes to the perception of trustworthiness. Notably, the use of language by VCAs in responding to customers, plays a more prominent role than virtual representations in creating a sense of human-likeness. Virtual representation such as Avatars in human form and naming the VCAs initially form trust, however that trust is short lived if the VCA does not have the ability to perform the required task. These insights underscore the nuanced ways in which anthropomorphic features influence the trusting intentions of customers.

Limitation and Future Research

Limitations

The study focused on a qualitative view on understanding the how human trustors perceive the ABI trustworthiness antecedents based on anthropomorphised. Literature has indicated that anthropomorphic features contribute to trustworthiness antecedents in aggregate. Participants would provide contradictory perspectives on whether anthropomorphic features were eerie or contributed to the development of trust (Lalot & Bertram, 2024). The assessment of trustworthiness still lacked clarity on which object of trust was considered in reaching a trust decision whether it was the organisation or the people behind the AI (developers). Further the study excluded age

groups below 18 years. This age group could be more predisposed to trusting in AI than older generations.

Recommendations for Future Research

This study highlights the critical role of anthropomorphism in customer engagement with chatbots. However, conflicting views exist regarding whether customers of financial services institutions (FSIs) perceive anthropomorphism as a key factor in assessing chatbot trustworthiness. Future research should examine whether anthropomorphism directly influences trust or primarily affects AI engagement. Additionally, studies should explore whether customers perceive trustworthiness antecedents directly in relation to the chatbot or if this relationship is mediated by trust in the developers or the organisation. Further investigation is needed to determine whether customers place greater emphasis on the anthropomorphic features of the brand or organisation rather than those of the AI when forming trust judgments.

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Appendix A: Description of Participants

#	Participant Code	Age	Customer/Expert	Interview Duration
C1	BM48Lecturer	48	customer	30 min, 38 seconds
E2	BF41Entreprenuer	41	expert chatbot developer	44 min, 50 seconds
C3	BF30SeniorActurialAnalyst	30	customer	01 hour, 17 minutes, 23 seconds
C4	BF44Projectcoordinator	44	customer	43 minutes, 19 seconds
C5	BF25Quantiativeanalyst	25	customer	19 minutes, 14 seconds
C6	BF42SeniorFinancialManager	42	Customer	43 minutes 15 seconds
C7	BM38SeniorManagerBusinessImprovement_design	38	customer	46 minutes, 03 seconds
C8	BM67retireddeveloper	67	customer	49 minutes, 34 seconds
C9	BF39FranchiseManager	39	customer	47 minutes, 06 seconds
C10	BM44Headofdatamanagementandgovernance	44	customer	57 minutes 25 seconds
C11	BF40Seniorlecturer	40	customer	51 minutes 20 seconds,
C12	BF40HeadofDepartment	40	customer	47 minutes, 33 seconds

C13	MRC54Qualitymanager	54	customer	57 minutes and 4 seconds
C14	BF37Traincontroller	37	customer	59 minutes,09 seconds
E15	MRCM43Entrepreuener	43	expert _ Financial Advisor	58 minutes 33 seconds
C16	BM28ManagerConstruction	28	customer	58 minutes 22 seconds
C17	BF46Bookkeeper	46	customer	01 hour, 02 minutes, 54 seconds
C18	BM23InternSoftwaredeveloper	23	customer	57 minutes, 46 seconds
C19	BF42Trainingmanager	42	customer	59 minutes, 56 seconds
C20	WF40FictionAuthorcorporatecommunicaiton marketing and	40	customer	58 minutes, 17 seconds
C21	BF40Projectmanager	40	customer	44 minutes, 35 seconds
C22	BF40Nurse_Customer	40	customer	59 minutes, 26 seconds
C23	WF38Entrepreuener	38	customer	48 minutes, 50 seconds
C24	BF43ManagerFinancialAccouintgandCompliance	43	customer	59 minutes, 49 seconds
C25	BF41Entrepreuener	41	customer	53 minutes, 52 seconds
C26	WM38Pastor	38	customer	48 minutes 18 seconds

				Made out of two recordings
C27	BF31Continuousimprovementspecialist	31	customer	53 minutes, 40 seconds
E28	BF45headofcustomerexperience	45	expert	49 minutes, 35 seconds
29	BF41PhDcandidate	41	customer	26 minutes, 37 seconds
E30	BM34SeniorLecturer	34	Expert_ AI computer science	01 hour, 0 minutes, and 30 seconds
C31	BF32selfemployed	32	customer	1 hour, 5 minutes, 03 seconds
C32	BM23Internsoftwaredeveloper	23	customer	53 minutes, 30 seconds
C33	WM25Internsoftwaredeveloper	25	customer	59 minutes, 30 seconds
C34	BF28Customerconsultant	28	customer	35 minutes, 15 seconds
C35	BM26Softwaredeveloper	26	customer	40 minutes, 42 seconds
C36	BF32Mastersstudent	32	customer	40 minutes 7 seconds
C37	BF32Chemistspecialist	32	customer	49 minutes, 25 seconds
C38	WM23TechnicalAnalyst	23	customer	54 minutes, 52 seconds

C39	WM29DataEngineer	29	customer	01 hour, 18 minutes, 28 seconds
C40	BF43Seniorespecialisttelecommunication	43	customer	01 hour, 11 minutes, 09 seconds
C41	BF25_JuniorAnalytics engineer customer	25	customer	29 minutes, 25 seconds
C42	BF29_NetworkEngineer	29	customer	30 minutes, 43 seconds
E43	BF40_ManagerProductdevelopment_expert	40	expert Product development	54 minutes, 48 seconds
C44	BF28_Managerservicedelivery	28	customer	1 hour, 1 minute and 14 seconds
C45	BF27customerserviceconsultant	27	customer	30 minutes, 8 seconds
C46	BF46ActingChieftechonologyandinformation officer	46	customer	50 minutes, 19 seconds
C47	BF30Customofficer	30	customer	40 minutes, 0 seconds
C48	WM40Applicationsdeveloper	40	customer	45 minutes, 45 seconds
C49	BM50ChiefOperatingOfficer	50	customer	45 minutes, 4 seconds
E50	BM41Productmanager	41	Expert Product Manager	58 minutes, 22 seconds
C51	BF40Shiftmanager	40	customer	47 minutes, 18 seconds

C52	BF51financemanager	51	customer	49 minutes, 08 seconds
E53	WM60ChiefAIofficer	60	expert	58 minutes, 47 seconds
C54	WM37Logisticsmanager	37	customer	41 minutes, 35 seconds
C55	BF20student	20	customer	32 minutes, 46 seconds
C56	BF44Investor	44	customer	44 minutes, 16 seconds
C57	BM43Programmemanager	43	customer	52 minutes, 59 seconds
C58	BF44ITsupport	44	customer	01 hour, 2 minutes, 30 seconds
C59	MRCF42Entrepreneur	42	customer	55 minutes,53 seconds
C60	IM41DevelopmentFinancier_customer	41	customer	42 minutes, 11 seconds
C61	WM43Entrepreneur_customer	43	customer	55 minutes,58 seconds
C62	WF55GroupCompliance	55	customer	52 minutes, 53 seconds
C63	WF28Economist	28	customer	53 minutes, 51 seconds
E64	BF35_customer experience manager	35	expert	55 minutes, 20 seconds
C65	IM52_Lecturer	52	customer	41 minutes, 46 seconds

C66	MRF54_Head of remuneration	54	customer	52 minutes, 9 seconds
E67	IF48_digital delivery expert	48	expert	56 minutes, 17 seconds
C68	MRF30_doctor	30	customer	59 minutes, 39 seconds
C69	BM28ProjectManager	28	customer	38 minutes, 46 seconds
C70	BM35Registrar	35	customer	54 minutes, 4 seconds
C71	BM28_ProcuretoPay Analyst	28	customer	33 minutes, 19 seconds
C72	BM28_Projectcoordinator	28	customer	37 minutes, 32 seconds
C73	BM39_Lecturer	39	customer	53 minutes, 29 seconds
C74	BM28_Trainingofficer	28	customer	45 minutes, 0 seconds
C75	BM27_Mastersstudent	27	customer	35 minutes, 41 seconds
C76	BM28_Cybersecurityofficer	28	customer	31 minutes, 7 seconds
C77	BM31_NetworkInfrastructure specialist	31	customer	36 minutes, 14 seconds
C78	BM26_HospitalStockController	26	customer	29 minutes, 21 seconds
C79	BM30_Watermanagement process controller	30	customer	38 minutes, 46 seconds

C80	BM28_Auditcompliance officer	28	customer	35 minutes, 30 seconds
C81	BM29_System_Analyst	29	customer	50 minutes, 34 seconds
C82	BM28UserExperienceDesigner	28	customer	27 minutes, 24 seconds
C83	BM27UserExperienceDesigner	27	customer	42 minutes, 23 seconds
C84	MRCF49Entrepreneur	49	customer	24 minutes, 16 seconds
C85	BM28Projectcoordinator	28	customer	37 minutes, 28 seconds
C86	BM26Entrepreneur	26	customer	22 minutes, 42 seconds
C87	BM30_Entrepreneur	30	customer	42 minutes, 24 seconds
C88	BM27_ITmanager	27	customer	41 minutes, 49 seconds
C89	BM28_InternPlantOperator	28	customer	30 minutes, 27 seconds
C90	BM31_Entrepreneur	31	customer	25 minutes, 14 seconds
C91	MRCF43_PlanningAdvisor	43	customer	30 minutes, 12 seconds
C92	BM27_communications_manager	27	customer	55 minutes, 28 seconds