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Rethinking Conversation Styles of Chatbots from the Customer Perspective: Relationships between Conversation Styles of Chatbots, Chatbot Acceptance, and Perceived Tie Strength and Perceived Risk

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ABSTRACT
Grounded in the Stereotype Content Model, Risk Perception Theory, Technology Acceptance Model, and Relational Embeddedness Theory, this research delves into the relationship between chatbot conversation styles, customer risk, and the mediating role of chatbot acceptance and tie strength in online shopping. A 2 (warm *vs.* cold) * 2 (competent *vs.* incompetent) between-subjects experiment is conducted on 320 participants and the results obtained from two-way ANOVA and PROCESS macro revealed that: (a) customer-perceived risk decreases with conversation warmth rather than conversation competence; (b) customer acceptance of chatbots improves with conversation competence rather than conversation warmth, while not acting as an intermediary factor between the conversation styles and customer-perceived risk; (c) customer perceived tie strength increases with both conversation warmth and conversation competence. The findings contribute to the existing literature about the impact of chatbot anthropomorphism on customer cognitive processes and offer executives insights into the design of customer-friendly chatbots.

KEYWORDS
Customer-chatbot interaction; chatbot anthropomorphism; customer risk perception; chatbot acceptance; perceived tie strength

1. Introduction

A "chatbot tsunami" is spreading across industry sectors (Grudin & Jacques, 2019) and is transforming customer service. Like self-driving cars and robots, chatbots are a specific segment of artificial intelligence (AI) that are defined as computer programs that simulate the cognition and affection of humans (Russell et al., 2010). Correspondingly, anthropomorphism is defined as the tendency for non-human agents to be equipped with human-like characteristics, motivations, intentions, or emotions (Epley et al., 2007). The two preceding definitions together predict the unavoidable future for chatbots to become increasingly human-like. In their early phase of development, they were mostly treated as inanimate machines, fulfilling objective tasks, such as information search and timetable scheduling. However, they are presently equipped with more human-like characteristics, such as warmth, humor, empathy, sensitivity, and conversation delays (Crolic et al., 2022; Liu et al., 2022; Moriuchi et al., 2021; Schanke et al., 2021). Initial efforts to understand the outcomes of chatbot anthropomorphism found that it positively affects customer purchase behavior, brand engagement, recommendation acceptance, and asset allocation (Hildebrand & Bergner, 2021; Luo et al., 2019; McLean et al., 2021).

Whilst anthropomorphism may have a positive impact, interaction with a novel technology designed to mimic human behavior may generate risk perception among consumers. Understanding risk perception is crucial for conducting business, as it plays a significant role in customer decision-making (Marriott & Williams, 2018; Min & Cunha, 2019). Despite that, current research on risk perception toward chatbots is not very prolific and neglects the impact of anthropomorphism. On the contrary, technology acceptance has been widely explored in literature. The relationship between anthropomorphism and perceived risk could be studied through acceptance, as it serves as a predictor of behavioral intention, performance, and consumer perception (Abdullah & Ward, 2016; Chen et al., 2020; Lunney et al., 2016; Nikou & Economides, 2017; Oyman et al., 2022). However, existing literature on technology acceptance focuses on non-human-like technologies and there is limited research that examines the relationship between chatbot anthropomorphism, risk perception, and acceptance. The anthropomorphic characteristics of AI devices are found to be positively associated with customer acceptance (Pelau et al., 2021), providing a foundation for further investigation into customer risk perception and acceptance levels in relation to increasingly anthropomorphic chatbots.

Besides anthropomorphism, the capacity of AI-driven chatbots to engage in complex dialogues emulates the sensation of interacting with a human being. This is referred to as "automated social presence" (van Doorn et al., 2017) and is the extent to which technology can make customers feel the presence of another social entity. Research has shown

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that social presence is a key factor in shaping customer perceptions, such as customer loyalty, sharing intentions, purchasing behavior, and service quality evaluation (Konya-Baumbach et al., 2023; Liu & Wei, 2021; Munnukka et al., 2022). The advent of automated social presence introduces a novel framework for understanding social interactions between customers and other social entities. (Panagopoulos et al., 2017; Ryu & Feick, 2007; Shen et al., 2016; Umashankar et al., 2017; Yim et al., 2008). However, existing literature rarely views AI-driven chatbots as entities with social roles, seldom embedding them in social networks. Furthermore, perceived risk is found to be transferable between social entities (Liao & You, 2014), which raises the question of whether the former can be adapted to chatbots with social roles and social networks.

Increasing adoption of chatbots modified the pre-existing consumer relationship dynamics and introduced new challenges, such as the perceived privacy risk toward chatbots (Cheng & Jiang, 2020). Examining the pre-decision cognitive process of the consumers is crucial for understanding their perception of chatbots. There are various studies that address this topic by measuring the risk perception and technology acceptance of customers, but they do not take anthropomorphism into account. Therefore, the first goal of this study is to understand the effect of anthropomorphism on risk perception and technology acceptance as there is a lack of research. On top of that, this study further aims to answer whether the relationship between risk perception and anthropomorphism is achieved through acceptance since risk perception behaves as a dimension of technology acceptance (Kamal et al., 2020; Kesharwani & Bisht, 2012; Wang et al., 2018). With increasing human likeness and intelligence, the social embeddedness of AI-driven chatbots is getting deeper, despite the lack of research about it in academia. As a second goal, this article aims to address the gaps in the existing literature regarding the social presence of chatbots by: (a) embedding chatbots in customer-salesperson social networks under the background of Relational Embeddedness Theory (RET), and (b) investigating how this network affects the risk perception of customers.

2. Literature review

2.1. Chatbot anthropomorphism and stereotype content model

Artificial intelligence refers to computer programs that simulate the cognition and affection of humans (Russell et al., 2010), and chatbots are a branch of AI systems designed to mimic human-to-human conversations using natural language (Griol et al., 2013; Sucameli, 2021). To overcome miscommunication by simulating realistic conversation scenarios, the anthropomorphism of chatbots has become a hotspot in academia recently (Kim & Im, 2023; Konya-Baumbach et al., 2023; Munnukka et al., 2022; Rhim et al., 2022). Anthropomorphism is defined as the tendency to imbue nonhuman agents with humanlike characteristics, motivations, intentions, or emotions (Epley et al., 2007). Chatbot anthropomorphism can be improved through three aspects, visual cues (figure, avatar, and gender), identity cues (name, identity, and disclosure), and communicational cues (human language mimicking) (Go & Sundar, 2019). Communicational cues and visual cues (in the form of emoticons) are investigated in this study as conveyors of anthropomorphism for text-based chatbots.

To assess the reaction of customers to the anthropomorphic traits of chatbots and how they perceive different variations of communicational cues, this study utilized the Stereotype Content Model (SCM). SCM is a classification of people's traits into two dimensions based on others' perceptions: warmth (*vs.* coldness) and competence (*vs.* incompetence) (Fiske et al., 1999). A warm conversation style that includes more emotional words is seen as much friendlier, kind, and more enthusiastic than a cold conversation style, while a competent conversation style, which includes more functional words, is viewed as more capable, effective, and intelligent compared to an incompetent style. This model has been shown to reliably differentiate human traits for individuals and groups (Cuddy et al., 2009; Durante et al., 2017) and even for lifeless objects, such as products, organizations, and countries (Aaker et al., 2010; Motsi & Park, 2020). The conversation style has a significant impact on participants' evaluation of the communication and their perceptions of each other (Thomas et al., 2018). In recent studies, it has been shown that the SCM can also be applied to the interactions between chatbots and humans: warm conversation messages from chatbots have been shown to improve brand engagement in contrast to competent messages (Kull et al., 2021), and customer experience can be improved through the output of warm dialogs from chatbots (Roy & Naidoo, 2021). The objective of this study is to investigate how consumer risk perception varies across different communication styles of chatbots within the Stereotype Content Model (SCM) dimensions.

2.2. Risk perception theory and anthropomorphism

The perceived risk that comes from uncertainty during the shopping process is not an objective measurement but a subjective perception varying with personalities and environmental cues (Bauer, 1960). Due to the increased popularity of online shopping, the origins and consequences of risk perception in e-commerce have become more popular in the literature. Shopping frequency and trust influence risk perception (Mortimer et al., 2016), and perceived risk is found to be significantly correlated with customer trust, satisfaction, impulse buying, repurchase intention, and brand loyalty (Hasan et al., 2021; Martin et al., 2015; Tandon et al., 2017; Wu et al., 2020). However, only very few studies explore the antecedent of risks in chatbot usage. Customer-perceived risk is shown to differ between chatbots and human agents (Song et al., 2022). Even in human-to-human interactions, the degree of similarity in conversation style between the agent and the customer directly impacts the effort needed to accomplish the task (Thomas et al., 2018). Trivedi (2019) focuses on the relationship between perceived risk and system quality, information quality, and service quality of chatbots, but the study is specialized for the banking industry. Kasilingam (2020) connects perceived risk with intentions to use chatbots, but he does not consider the effect of increasing anthropomorphism of chatbots.

With the two dimensions proposed in the SCM model, this research examines how warm *vs.* cold and competent *vs.* incompetent styles of chatbots affect the perceived risk of customers. A warm conversation style could satisfy the customer's need for interpersonal conversation by generating sentences with emotional cues. On the other hand, conversation capability is highly related to adoption intention (Song et al., 2022), so a competent conversation style is expected to reduce customer-perceived risk by showing the ability to fulfill tasks. Warmth and competence are found to amplify each other in interpersonal judgments (Cuddy et al., 2008), while brand engagement increases with warm messages but not with competent messages (Kull et al., 2021). Furthermore, the perception of a chatbot's competence and warmth differ with visual cues and the level of message interactivity (Huang et al., 2021). Despite being separate dimensions, warm and competent communications are intertwined and argued to moderate each other on customer risk perception. Therefore, this research proposes the following hypotheses:

H1: The warm communication style of chatbots leads to lower customer-perceived risk than the cold conversation style.

H2: The competent communication style of chatbots leads to lower customer-perceived risk than the incompetent conversation style.

H3: The interaction effect between the warm (vs. cold) and competent (vs. incompetent) conversation styles of a chatbot has a bearing on customer-perceived risk.

2.3. The relationship between communication styles of chatbots, chatbot acceptance, and customer perceived risk

Technology acceptance is influenced by perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). Perceived usefulness refers to the degree to which a person believes that using a particular system would enhance the performance and perceived ease-of-use refers to the degree to which a person believes that using a new technology will be free of effort. Business processes have been transformed by new technologies to a large extent over decades and TAM continues to be a robust theory for explaining people's reactions toward new technologies, such as e-commerce, interactive dressing rooms, and mobile applications (Ashraf et al., 2014; Huang et al., 2019; Kim et al., 2017; Vahdat et al., 2021). Despite the proven effectiveness of technology acceptance, there are not many studies in the literature regarding the relationship between chatbot anthropomorphism and acceptance as most studies focus on non-human-like technologies.

People's reluctance to accept the usage of AI for subjective tasks, known as algorithm aversion, is often driven by the belief that algorithms lack necessary human-like emotions (Castelo et al., 2019). Anthropomorphism can be the key to reduce this bias as it has been found to increase the acceptance of AI devices (Pelau et al., 2021). Warmth has the potential to increase people's willingness to adopt AI (Roy & Naidoo, 2021) and competent messages from chatbots that demonstrate the ability to fulfill tasks can directly influence chatbot acceptance (Song et al., 2022). Thus, chatbots that exhibit anthropomorphic characteristics, such as warmth and competence in their conversation styles, have the potential to increase people's willingness to adopt AI and overcome algorithm aversion.

In addition to PEOU and PU, perceived risk has been connected with TAM: it serves as a determinant of individuals' adoption intention toward telemedicine services and internet banking (Kamal et al., 2020; Kesharwani & Bisht, 2012). Furthermore, it elucidates users' behavioral intentions concerning ride-sharing services (Wang et al., 2018). Risk perception and technology acceptance are not only confined to consumer attitudes toward a certain technology but can also be transferred to other entities, such as brands (Hasan et al., 2021). Acceptance of technology and e-services can also play a mediating role in risk perception, reducing risk concerns to some extent (Featherman & Pavlou, 2003). Thus, the following hypotheses are formed for technology acceptance:

H4: The warm communication style of chatbots leads to higher chatbot acceptance than the cold communicational style.

H5: The competent communication style of chatbots leads to higher chatbot acceptance than the incompetent communication style.

H6: The effect of warm (vs. cold) conversation style on customer perceived risk is mediated by chatbot acceptance.

H7: The effect of competent (vs. incompetent) conversation style on customer perceived risk is mediated by chatbot acceptance.

2.4. The relationship between conversation styles of chatbots, perceived tie strength, and customer perceived risk

According to Relational Embeddedness Theory (RET), social and emotional outcomes are intertwined with economic outcomes in a social system, and economic activities are connected through the relationships between the participants (Granovetter, 1973). The strength of the relationship tie between individuals is found to change people's attitudes toward ads and sharing intention, directly influencing conversation effectiveness for advertisements (Shen et al., 2016). A strong perception of tie strength between salespersons and customers not only works as a guarantee for sales performance from individual clients (Panagopoulos et al., 2017) but also is an important factor of commitment to firms (Stanko et al., 2007). A strong tie facilitates customer loyalty after customer complaints (Umashankar et al., 2017) and

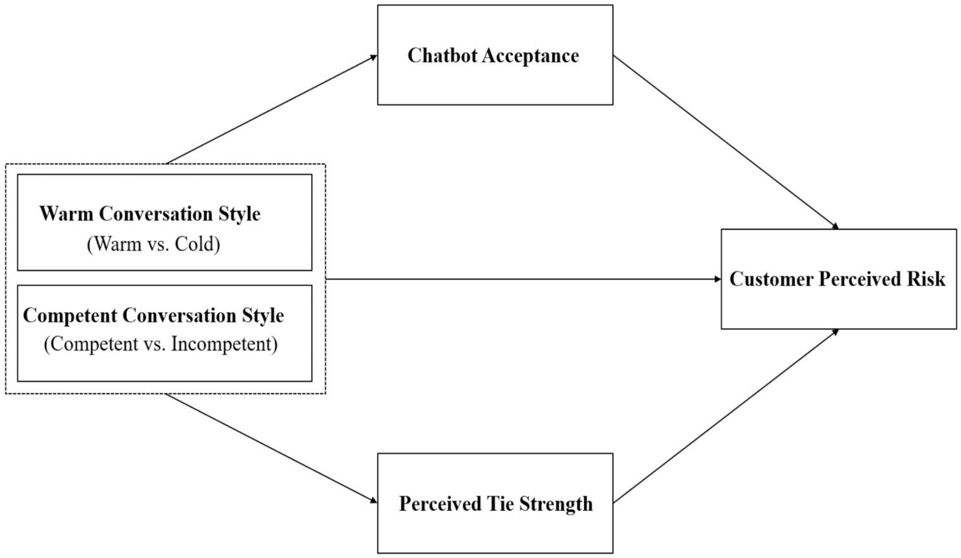

Figure 1. Conceptual model.

Table 1. Conditions for the experiment.

Condition	Description	Stimuli
1	Warm * Competent	Emoticons and warm words * effective responses
2	Warm * Incompetent	Emoticons and warm words * ineffective responses
3	Cold * Competent	No emoticons and cold words * effective responses
4	Cold * Incompetent	No emoticons and cold words * ineffective responses

mitigates perceived distribution unfairness of buyers (Lee & Griffith, 2019).

Castaldo et al. (2010) discovered that competence can increase trust and benefit network involvement, which is aligned with what RET proposes. The way a person converses reveals their personality and shapes how the conversation partner perceives the relationship (Pennebaker, 2011), so different conversation styles employed by salespersons are expected to alter the perception and emotions of customers. In the context of e-commerce, the emotional power between chatbots and customers is analogous to that between salespersons and customers; with the onset of affective exploration, chatbots, and human beings can develop relationships (Skjuve et al., 2021). Displaying emotions stimulates emotional bonds between users and machines (Rincon et al., 2019); expressing surprise and happiness has been found to positively impact customer perception toward chatbots (Chuah & Yu, 2021). Therefore, emotional power cannot be denied in human–chatbot interactions. Furthermore, the emotional tie is a factor that influences risk perception, as it is correlated with customer trust, satisfaction, and brand loyalty (Hasan et al., 2021; Martin et al., 2015; Mortimer et al., 2016; Tandon et al., 2017; Wu et al., 2020). Given that the perceived risk is transferable between social entities (Liao & You, 2014), it can be hypothesized that perceived tie strength mediates the process from conversation styles to the perceived risk. Therefore, the following hypotheses are formed:

H8: The warm communication style of chatbots leads to a higher perceived tie strength than the cold communicational style.

H9: The competent communication style of chatbots leads to a higher perceived tie strength than the incompetent communication style.

H10: The effect of warm (vs. cold) conversation style on customers' perceived risk is mediated by perceived tie strength.

H11: The effect of competent (vs. incompetent) conversation style on customers' perceived risk is mediated by perceived tie strength.

The conceptual framework of this article is shown in Figure 1.

3. Methodology

3.1. Stimuli and conditions

This study used 2 (warm *vs.* cold) * 2 (competent *vs.* incompetent) between-subjects factorial experiment design (see Table 1). Stimuli for warm conversation style were conveyed by emoticons like "(*^▽^*)" and words like "friendly, glad, surprise and free" in dialogs, while dialogs for cold conversation style abandoned all emoticons and words that expressed warmth and friendliness. Stimuli for competent conversation style were conveyed by understanding and responding to customers' questions precisely whereas stimuli for incompetent conversation style were shown by outputting words and phrases like "I don't quite understand what you mean" and "I will direct you to human services" (see

Appendix A). The pre-purchase dialogs between customers and chatbots about a fictitious brand's ("Virtus") smartphone were inquired. Participants received screenshots of the dialogs based on the condition they were randomly assigned to and were asked to fill out a survey to assess their perception. This study chose screenshots as stimuli carriers since the effectiveness of screenshots to convey information for experiments is confirmed (Chocarro et al., 2021; Roy & Naidoo, 2021).

3.2. Experiment design

The experiment excluded the influence of chatbot identity disclosure, name, gender, and avatar (Borau et al., 2021; Go & Sundar, 2019; Luo et al., 2019). The identity of the chatbots was disclosed to subjects at the beginning of the survey, and they were given the same cartoon robot avatar and the same name, "Virtual Shopping Assistant." Gender cues were not used throughout the entire process (see Appendix A). The experiment uses smartphones to keep the product category consistent (Roy & Naidoo, 2021) and a fictitious brand name "Virtus" to avoid the noise of risk perception about existing brands (Kwak et al., 2015; Puzakova & Kwak, 2017).

Risk perception has been shown to vary with customer demographic heterogeneity, such as age, income, educational level, risk aversion (Holt & Laury, 2002; Schiffman, 1972; Sharma & Kurien, 2017), and exterior heterogeneity, such as prior experience (Kasilingam, 2020). Demographic heterogeneity was kept consistent by choosing participants among university students who had a limited scope of age, income level, and educational level. The questionnaire identified prior experience with online shopping and chatbots, and samples lacking either were excluded from the study. Risk aversion was regarded as a control variable for this experiment.

Four chatbots representing four experiment conditions were customized by Alibaba Cloud Services and screenshots were taken as experiment materials (see Appendix A). The online survey was distributed by Qualtrics links *via* WeChat and WhatsApp platforms. First, subjects were placed in a scenario in which they planned to buy a smartphone through chatbot assistants. After being exposed to one of four conversation screenshots, participants were asked to answer 8 manipulation check questions about the conversation style of the chatbot (see Appendix B). Second, participants answered questions related to mediator variables (chatbot acceptance and perceived tie strength) and the dependent variable (perceived risk). Finally, data about risk aversion and participants' demographic information (age, gender, disposable income, educational level, prior experience with online shopping, and chatbot interaction) were collected. Each item (including the manipulation check questions) was measured by a seven-point Likert scale, ranging from 1 (*totally disagree*) to 7 (*totally agree*) (see Appendix C).

3.3. Risk perception and tie strength dimensions

Originally composed of two dimensions, scholars enriched the risk perception theory into a six-dimensional comprehensive model that includes financial risk, functional performance risk, physical risk, psychological risk, social risk, and time risk (Cunningham, 1967; Peter & Tarpey, 1975; Roselius, 1971). Performance risk, financial risk, and psychological risk are dimensions that are proven to significantly influence customer behavior in e-commerce (Qalati et al., 2021; Sharma & Kurien, 2017), whereas social risk and physical risk were found to be insignificant (Featherman & Pavlou, 2003; Kamalul Ariffin et al., 2018). Chatbots are prone to trigger specific dimensions given their unique characteristics compared to humans, and the perceived privacy risk associated with them has been shown to reduce customer satisfaction (Cheng & Jiang, 2020). As a consequence, the following dimensions are taken into account in this study: (a) performance risk; (b) financial risk; (c) psychological risk; and (d) privacy risk.

Relationship tie strength is measured across four dimensions: mutual confiding, relationship length, emotional intensity (closeness), and reciprocal service. Intimacy (closeness) is the most important representative of relationship strength, while connection time and frequency tend to overestimate user perception (Marsden & Campbell, 1984). During this research, tie strength is examined across the following dimensions: (a) closeness; (b) mutual confiding; and (c) reciprocity.

3.4. Pretest

A pretest was conducted among university students in China and Netherlands, and all subjects were assigned randomly and evenly to one of four screenshots corresponding to the four experimental situations (see Appendix A). After deleting 13 samples with missing data, there were 120 valid feedbacks in total (N male = 79; N female = 41). 91.7% of participants were 18–25 years old.

Results of one-way ANOVA showed that people assigned to the warm conversation style reported more warmth, friendliness, kindness, and enthusiasm than those who were assigned to the cold conversation style [$M_{\text{warm}} = 5.21$ *vs.* $M_{\text{cold}} = 3.43$, $F\ (1{,}118) = 63.64$, $p < 0.001$]. Similarly, screenshots with a competent conversation style are perceived as more competent, capable, effective, and intelligent than those with an incompetent conversation style [$M_{\text{competent}} = 5.39$ *vs.* $M_{\text{incompetent}} = 2.28$, $F\ (1{,}118) = 143.18$, $p < 0.001$].

Reliability tests and validity tests were performed on each construct of the scale. Regarding the dependent variable, the item, "I would be concerned that the product recommended by the chatbot may not perform to my expectations" was decided to be deleted because of the low extraction value of .49 and component score coefficient of .09. The remaining 11 items of risk perception passed the reliability and validity tests (Cronbach's $\alpha = .950$; KMO = .879, $p < 0.01$). As for mediators, both chatbot acceptance (Cronbach's $\alpha = .953$; KMO = .891, $p < 0.01$) and perceived tie strength (Cronbach's $\alpha = .945$; KMO = .889, $p < 0.01$) had satisfied reliability and validity. For risk aversion (Cronbach's $\alpha = .929$), after deleting the most irrelevant item, "when I shop online, I would like to go for a well-known brand," the KMO value and the accountability of variance increased from .553 and 76.36% ($p < 0.01$) to .768 and 87.94% ($p < 0.01$), respectively. Ultimately, all the remaining items after optimization could be conducted to examine the hypotheses (see Appendix C).

3.5. Participants and manipulation check

There were 368 samples in total. Three responses with participants being younger than 18 years old and 17 samples with missing data were filtered out. Two respondents were unqualified for having prior experience in online shopping and 26 respondents did not have any prior chatbot interaction, therefore they were excluded too. The ultimate sample size was 320 which consisted of 62 participants (19.4%) from the Netherlands and 258 (80.6%) from China and 175 males (54.7%) and 145 females (45.3%). Since most participants were university students, 19–25-year-old participants were the largest group which accounted for 73.8% of the population. Correspondingly, 91.3% of participants had at least a Bachelor's degree. 67.6% of subjects have a disposable income below 600 euros and over 20% of subjects have a disposable income higher than 800 euros. Students recruited from China had quite different financial statuses from students recruited from the Netherlands, therefore disposable income has the largest standard deviation. Nevertheless, no significant impact on the main variable was detected regarding the two sample groups.

After selecting and assembling the participants, a manipulation check is applied for chatbot conversation styles (see Appendix B). Results of one-way ANOVA show that compared with those exposed to cold conversation scenarios, participants exposed to warm conversation scenarios reported that chatbots are more warm, friendly, kind, and enthusiastic [$M_{\text{warm}} = 5.15$ *vs.* $M_{\text{cold}} = 3.28$, F (1,318) = 219.84, $p < 0.001$]. Likewise, subjects allocated to competent conversation screenshots perceived more competence, capability, effectiveness, and intelligence than those assigned to incompetent conversation screenshots [$M_{\text{warm}} = 6.02$ *vs.* $M_{\text{cold}} = 1.80$, F (1,318) = 985.88, $p < 0.001$]. It is safe to conclude that the manipulation of chatbot conversation styles was successful.

3.6. Measurements

The dialogs represented different conversation styles referred to by Roy and Naidoo (2021). Eight manipulation check questions were based on Aaker et al. (2010) and Kull et al. (2021); items of customer perceived risk were adjusted based on Cheng and Jiang (2020) and Hong (2015); chatbot acceptance had three items based on Kasilingam (2020) and Rese et al. (2020); for the perceived tie strength, findings from Ryu and Lee (2017) and Stanko et al. (2007) shaped the items; the scale of customer risk aversion (control variable) originated from Tzeng and Shiu (2019). All items passed reliability and validity tests (see Table 2).

4. Results

4.1. Correlation matrix

Initially, a Pearson correlation analysis was conducted between all variables. Warm conversation style was correlated to all mediators and the dependent variable, and it correlated closer with customer-perceived tie strength (.700**) than chatbot acceptance (.572**). The competent conversation style was strongly correlated with chatbot acceptance (.939**) and also with perceived tie strength (.660**) whereas it was not correlated with the dependent variable. Customer-perceived risk is significantly correlated with risk aversion (.611**), proving the necessity to consider it as a control variable for the experiment (see Table 3).

4.2. Risk perception

People assigned to warm stimuli perceived fewer risks ($M = 5.34$, $SD = 1.10$) about online shopping than those

Table 2. Results of factor analysis for all variables.

Variables	Items	KMO	*df*	*p*-Value	Extracted factor	Eigenvalue	Variance explained (%)
Customer perceived risk	11	0.91	55	<0.001	1	7.2	65.49
Chatbot acceptance	6	0.886	15	<0.001	1	5.16	86.00
Tie strength	9	0.901	36	<0.001	1	6.27	69.69
Risk aversion	3	0.687	3	<0.001	1	2.42	80.75

Note: $N = 320$.

Table 3. Means, standard deviations, and Pearson correlation coefficients for all variables.

	Variables	1	2	3	4	5	6
1	Warm (*vs.* cold) conversation style	1	.528**	.572**	.700**	.328**	.121*
2	Competent (*vs.* incompetent) conversation style	.528**	1	.939**	.660**	.096	.003
3	Chatbot acceptance	.572**	.939**	1	.754**	.210**	.047
4	Perceived tie strength	.700**	.660**	.754**	1	.330**	.039
5	Customer perceived risk	.328**	.096	.210**	.330**	1	.611**
6	Risk aversion	.121*	.003	.047	.039	.611**	1
	Mean	4.21	3.90	4.04	3.62	5.49	5.91
	SD	1.46	2.43	1.97	1.46	1.03	.80

Notes: $N = 320$.
*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

assigned to cold stimuli ($M = 5.63$, $SD = 0.92$) at a significant level ($M_{dif} = -.285$, $p < .05$). The similar output of two-way ANOVA [F (1, 315) = 10.1, $p < .05$, partial $\eta^2 = .031$] also revealed that people's risk perception about online shopping decreased with the conversation warmth. The first hypothesis was supported.

Surprisingly, the capability of chatbots was irrelevant to customers' risk perception [F (1, 315) = .00, $p = .963$, partial $\eta^2 = .000$]. Mean difference from competence ($M = 5.49$, $SD = .97$) to incompetence ($M = 5.48$, $SD = 1.08$) was statistically non-significant ($M_{dif} = .004$, $p = .963$). Thus, hypothesis 2 was not supported by this study.

According to the results [F (1, 315) = 2.93, $p = .088$, partial $\eta^2 = .009$], the interaction between the two conversation styles did not produce a statistically significant effect. Therefore, hypothesis 3 cannot be concluded. (see Tables 4, 5 and Figure 2).

4.3. Chatbot acceptance and the mediation effect on risk perception

Results of two-way ANOVA presented a notable gap in chatbot acceptance between competent and incompetent conversation styles [$M_{competent} = 5.72$ *vs.* $M_{incompetent} = 2.39$, F (1,316) = 802.61, $p < 0.001$, partial $\eta^2 = .718$]. It had a considerably large effect size of .718. Conversely, this phenomenon did not appear in warm and cold conversation styles [$M_{warm} = 4.07$ *vs.* $M_{cold} = 4.03$, F (1,316) = .117, $p = .732$, partial $\eta^2 = .000$]. Taken together, hypothesis 5 was supported whereas hypothesis 4 was rejected (see Tables 6, 7 and Figure 3).

In the second part, a series of regression analyses by PROCESS model 4, v4.1 (Hayes, 2022) was carried out to test H6 and H7. For warm conversation style, results provided evidence for the effect of warmth on customer perceived risk ($B = -.284$, $SE = .09$, $p < .05$, $CI_{95\%} = [-.46, -.11]$), but there is no evidence for the mediating effect of chatbot acceptance ($B = -.006$, $SE = .021$, $CI_{95\%} = [-0.05, 0.04]$). Thus, hypothesis 6 which claimed that the effect of conversation style (warm *vs.* cold) on customer-perceived risk is mediated by chatbot acceptance was rejected.

As for the competent conversation style, despite the fact that direct ($B = 1.12$, $SE = .16$, $p < .001$) and indirect paths ($B = -1.12$, $SE = .13$, $CI_{95\%} = [-1.40, -.89]$) were both proven to be significant, results of total effect revealed an irrelevance between conversation competence and perceived risk ($B = .006$, $SE = .09$, $p = .94$), which was consistent with the conclusion of hypothesis 2. Because of the absence of a causal relationship between independent and dependent variables, the mediating effect disappeared simultaneously. Hence, the study rejected hypothesis 7 (see Figure 4).

Table 4. The output of pairwise comparisons for customer perceived risk.

	N	M	SD	$M_{difference}$	Sig.
Warm *vs.* cold conversation style					
Warm (I)	160	5.34[a]	1.10	−.285* (I-J)	<.05
Cold (J)	160	5.63[a]	.92	.285* (J-I)	<.05
Competent *vs.* incompetent conversation style					
Competent	159	5.49[a]	.97	.004 (I-J)	.963
Incompetent	161	5.48[a]	1.08	−.004 (J-I)	.963

*The mean difference is significant at the .05 level.
[a]Covariates appearing in the model are evaluated at the following values: Risk aversion = 5.9090.

4.4. Perceived tie strength and mediation effect on risk perception

H8, H9, H10, and H11 were examined by two-way ANOVA and PROCESS model 4, v4.1 (Hayes, 2022), respectively in the same way as chatbot acceptance. The dataset showed different levels of perceived relationship strength between warm and cold styles [$M_{warm} = 3.91$ *vs.* $M_{cold} = 3.33$, F (1,316) = 20.09, $p < 0.001$, partial $\eta^2 = .06$]. Likewise, there was a significant difference in customer-perceived tie strength between competent and incompetent styles [$M_{competent} = 4.44$ *vs.* $M_{incompetent} = 2.80$, F (1,316) = 162.47, $p < 0.001$, partial $\eta^2 = .34$]. Additionally, conversation competence had an effect size that was over medium (0.25) and close to large (0.4), while conversation warmth had a small effect size. To conclude, self-reported relationship strength positively varies with both warmth and competence. Therefore hypotheses 8 and 9 were supported (see Tables 8, 9 and Figure 5).

For warm utterances of chatbots, the total effect on perceived risk before adding perceived tie strength as a mediator was −.29 ($SE = .08$, $p < .05$, $CI_{95\%} = [-.46$ to $-.13]$). By adding perceived tie strength, the direct effect was −.20 ($SE = .08$, $p < .05$, $CI_{95\%} = [-.36, -.04]$) and the indirect effect was −.09 ($SE = .03$, $CI_{95\%} = -.14$ to $-.04$). Customer perception about tie strength contributed 31.3% to the path from warm style to risk perception. For the other path, the competent style had a

Table 5. Results of two-way ANOVA for customer perceived risk.

	Type III sum of squares	df	Mean square	F	Sig.	Partial eta-squared	Parameter estimates
Corrected model	133.762[a]	4	33.441	52.045	<.001	.398	
Intercept	4.689	1	4.689	7.298	<.05	.023	.838*
Risk aversion	122.078	1	122.078	189.995	<.001	.376	.775*
Warm *vs.* cold	6.487	1	6.487	10.096	<.05	.031	−.131
Competent *vs.* incompetent	.001	1	.001	.002	.963	.000	−.149
Warm *vs.* cold * competent *vs.* incompetent	1.882	1	1.882	2.928	.088	.009	.307
Error	202.398	315	.643				
Total	9970.215	320					
Corrected total	336.160	319					

$N = 320$.
Warm *vs.* cold * competent *vs.* incompetent refers to the interaction effects of the two conversation styles.
*$p < 0.05$.
[a]R squared = .398 (adjusted R squared = .390).

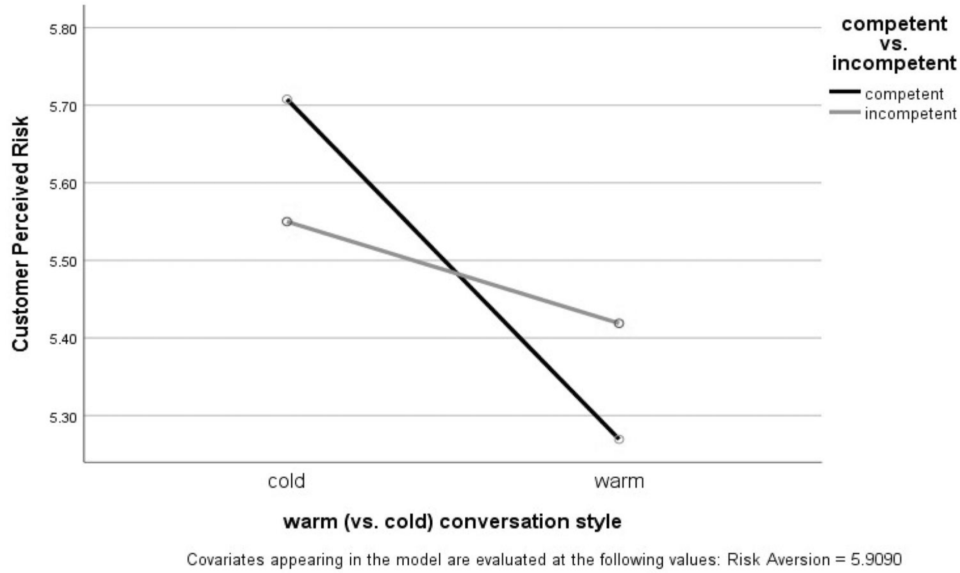

Figure 2. Interaction effects of warm (*vs.* cold) and competent (*vs.* incompetent) conversation styles for perceived risk.

Table 6. The output of pairwise comparisons for chatbot acceptance.

	N	*M*	*SD*	$M_{difference}$	Sig.
Warm *vs.* cold conversation style					
Warm (I)	160	4.07	2.03	.04 (I-J)	.732
Cold (J)	160	4.03	1.90	−.04 (J-I)	.732
Competent *vs.* incompetent conversation style					
Competent	159	5.72	.88	3.32* (I-J)	<0.01
Incompetent	161	2.39	1.19	−3.32* (J-I)	<0.01

*The mean difference is significant at the .05 level.

non-significant total effect on customer risk perception ($B = .01$, $SE = .08$, $p = .94$, $CI_{95\%} = [-0.16, 0.17]$). So, the mediation effect of perceived tie strength on risk perception was rejected simultaneously. To conclude, hypothesis 10 was confirmed while hypothesis 11 was rejected (see Figure 6).

4.5. Additional analysis

4.5.1. Components of risk perception

The research conducted additional analysis to provide readers with deeper insights. The first question was whether the effect of the warm conversation style on certain components of risk perception was too large, hiding the fact that it did not work on the other components at all. First, a two-way MANOVA was conducted to figure out the impact of conversation styles on each component of perceived risk. Product performance risk was excluded in additional analysis because it had only 2 items after optimization in the pretest and thus not satisfy data rigor and trustworthiness. Results showed that the warmth of chatbots in communications mainly worked on financial risk [$M_{warm} = 5.33$ *vs.* $M_{cold} = 5.64$, F (1,315) = 11.13, $p < 0.025$, partial $\eta^2 = .034$] and privacy risk [$M_{warm} = 5.57$ *vs.* $M_{cold} = 6.00$, F (1,315) = 23.22, $p < 0.01$, partial $\eta^2 = .069$] instead of psychological risk. Moreover, the conversation competence of chatbots did not impose an influence on any one of the three constructs (Tables 10 and 11).

4.5.2. Components of perceived tie strength

To have a better understanding of the human–chatbot relationship, it is necessary to clarify what constructs of perceived tie strength were the most influential. Likewise, three constructs of perceived tie strength, namely perceived closeness, mutual confiding intention, and reciprocity intention, were examined by two-way MANOVA. Surprisingly, there was no significant effect of conversation warmth on reciprocity [$M_{warm} = 4.12$ *vs.* $M_{cold} = 4.03$, F (1,316) = .433, $p = .511$, partial $\eta^2 = .001$]. Apart from that, all other constructs benefited from the conversation warmth and competence of chatbots (see Tables 12 and 13).

The study dived deeper into which constructs of perceived tie strength mainly undertook the mediation role from chatbot conversation warmth to customer-perceived risk. Results uncovered that only perceived closeness mediated the path ($B = -.33$, $SE = .08$, $CI_{95\%} = [-0.51, -0.17]$), while mutual confiding ($B = .07$, $SE = .04$, $CI_{95\%} = [-0.004, 0.16]$) and reciprocity ($B = -.01$, $SE = .03$, $CI_{95\%} = [-0.07, 0.04]$) showed no mediation effects.

5. Discussion

5.1. Main effects on customer perceived risk

In this study, warmth is found to play an important role in customer risk perception, especially for financial and privacy risks. The result is consistent with most of the extant findings in the literature. Brand warmth facilitates purchase intention (Kolbl et al., 2019) and chatbot warmth is beneficial for brand engagement (Kull et al., 2021). The underlying logic is that people have basic needs for interpersonal interactions and are prone to interact with highly anthropomorphic chatbots in a similar way (Sheehan et al., 2020). Meanwhile, warm messages enhance the anthropomorphism of lifeless objects, such as brands and chatbots, and change people's risk perception (Kim & McGill, 2011).

Table 7. Results of two-way ANOVA for chatbot acceptance.

	Type III sum of squares	df	Mean square	F	Sig.	Partial eta-squared	Parameter estimates
Corrected model	884.786[a]	3	294.929	267.761	<.001	.718	
Intercept	5255.672	1	5255.672	4771.550	<.001	.938	2.33*
Warm *vs.* cold	.129	1	.129	.117	.732	.000	.115
Competent *vs.* incompetent	884.044	1	884.044	802.611	<.001	.718	3.40*
Warm *vs.* cold * competent *vs.* incompetent	.442	1	.442	.402	.527	.001	−.149
Error	348.061	316	1.101				
Total	6461.417	320					
Corrected total	1232.847	319					

$N = 320$.
Warm *vs.* cold * competent *vs.* incompetent refers to the interaction effects of the two conversation styles.
$*p < 0.05$.
[a]R squared = .718 (adjusted R squared = .715).

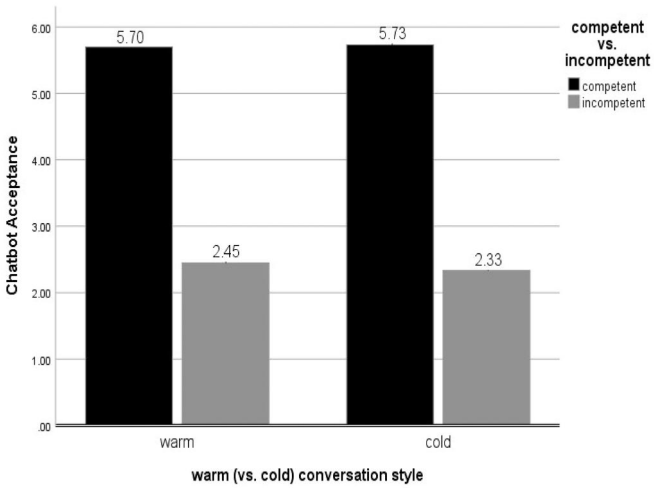

Figure 3. Mean comparisons of chatbot acceptance between warm (*vs.* cold) and competent (*vs.* incompetent) conversation styles.

Contrary to our expectations, the importance of chatbot competence for risk perception was negligible which is actually in accordance with findings in the literature. Unlike brand warmth, brand competence does not stimulate customer-brand identification (Kolbl et al., 2019). Similarly, brand engagement can be driven by conversation warmth instead of the conversation competence of chatbots (Kull et al., 2021). However, the conclusions of this research contradict findings regarding interpersonal interactions. The conversational competence of a salesperson is found to be a key driver of purchase intention and purchase behavior (Ihtiyar & Ahmad, 2014; Xu et al., 2016). The difference in attitude between human-machine and human-human interactions may be due to the identity disclosure of chatbots. Luo et al. (2019) found that identity transparency of chatbots before the conversation reduces the purchase rate by 79.7%. So, it is likely to leave a stereotype of incompetence for participants thus leading to a pre-perceived risk.

The underlying reason why chatbot identity causes such an evident difference can be due to people's stereotypes of chatbots rather than chatbot competence. Although chatbots virtually perform both objective and subjective tasks as well as humans, people don't trust chatbots regarding subjective tasks (Castelo et al., 2019). The distrust for subjective work can be broken by increasing chatbots' human-likeness. To sum up, enhancing conversation warmth and competence is a good way to counter the influence of chatbot identity, and the stereotypes against chatbots, such as they are not capable of performing subjective tasks, are expected to be reduced by human-level anthropomorphism.

5.2. Chatbot acceptance and the mediation effect on risk perception

Unlike in risk perception, the competence of the chatbots plays a role in their acceptance. Competent expressions are directly linked to chatbot acceptance because it signals the ability to fulfill tasks, which exactly corresponds to the two measurements of TAM: perceived utility and perceived usability (Davis, 1989). Because of the non-significant influence of competence on perceived risk, chatbot acceptance fails to mediate the effect. As mentioned above, this may be due to the pre-disclosure of chatbot identity, therefore the mediating role of chatbot acceptance should not be completely rejected by the findings of this study. Studies done in the past explicitly confirm the influence of competence on technology acceptance and the influence of acceptance on people's cognitive process including risk concerns (De Cicco et al., 2022; Featherman & Pavlou, 2003), and thus, mediating effects of chatbot acceptance is worthy of further exploration.

On the other hand, warmth is found to have a negligible effect on technology acceptance, and consequently, the mediating role of acceptance between warmth and risk perception is rejected by this study. This may be due to TAM estimating peoples' adoption intention merely from the technology utility and usability perspective (Davis, 1989), and not taking affection-related factors into consideration. The model proposed by Davis is applicable widely to most new technologies, such as online shopping, mobile application, and socially interactive dressing rooms (Ashraf et al., 2014; Huang et al., 2019; Kim et al., 2017). However, with the emerging concept of AI anthropomorphism nowadays, the model proposed in 1989 lags in evaluating the affection between humans and chatbots which is proven to exist (Rincon et al., 2019; Skjuve et al., 2021). An upgraded model (TAM3) extends the original TAM by stressing emotion-related components, such as perceived external control, playfulness, anxiety, and enjoyment (Venkatesh & Bala, 2008). Emotion-related cues of the algorithm are pointed to increase people's trust (Castelo et al., 2019), which is added to the original TAM model by Alalwan et al. (2018). All of these findings provide an up-to-date perspective to explore

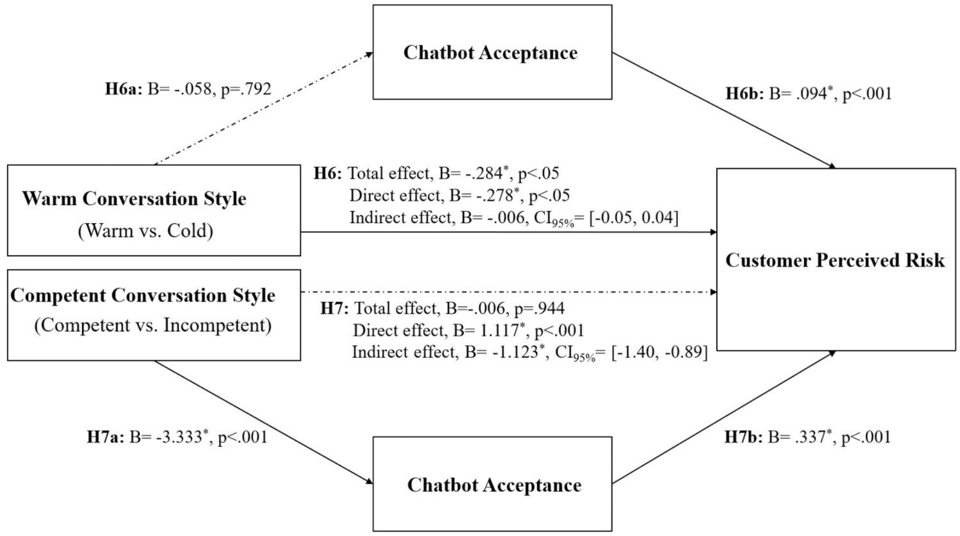

Figure 4. Mediation effects of chatbot acceptance.

Table 8. The output of pairwise comparisons for perceived tie strength.

	N	*M*	*SD*	$M_{difference}$	Sig.
Warm *vs.* cold conversation style					
Warm (I)	160	3.91	1.69	.579* (I-J)	<.001
Cold (J)	160	3.33	1.12	−.579* (J-I)	<.001
Competent *vs.* incompetent conversation style					
Competent	159	4.44	.88	1.646* (I-J)	<.001
Incompetent	161	2.80	1.19	−1.646* (J-I)	<.001

*The mean difference is significant at the .05 level.

Table 9. Results of two-way ANOVA for perceived tie strength.

	Type III sum of squares	*df*	Mean square	*F*	Sig.	Partial eta-squared	Parameter estimates
Corrected model	260.973[a]	3	86.991	65.227	<.001	.382	
Intercept	4192.346	1	4192.346	3143.470	<.001	.909	2.74*
Warm *vs.* cold	26.788	1	26.788	20.086	<.001	.060	.12
Competent *vs.* incompetent	216.675	1	216.675	162.465	<.001	.340	1.19*
Warm *vs.* cold * competent *vs.* incompetent	16.807	1	16.807	12.602	<.001	.038	.917*
Error	421.439	316	1.334				
Total	4866.494	320					
Corrected total	682.412	319					

$N = 320$.
Warm *vs.* cold * competent *vs.* incompetent refers to the interaction effects of the two conversation styles.
*$p < 0.05$.
[a]R squared = .382 (adjusted R squared = .377).

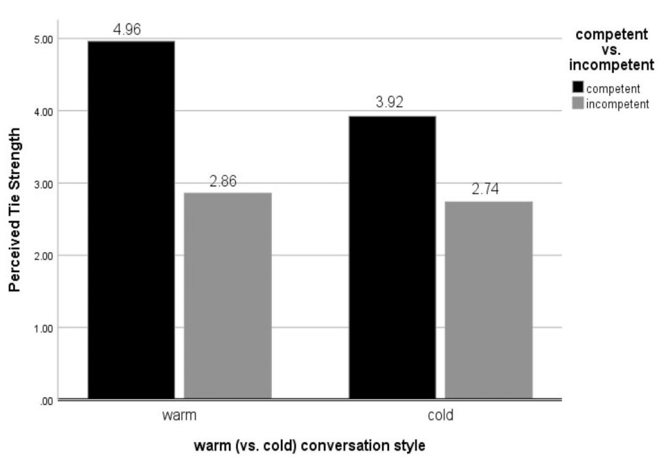

Figure 5. Mean comparisons of perceived tie strength between warm (*vs.* cold) and competent (*vs.* incompetent) conversation styles.

how emotion works in the acceptance of increasingly anthropomorphic chatbots and raise the question of whether the findings of this article would differ by utilizing TAM3.

5.3. Perceived tie strength and the mediation effect on risk perception

Like the relationship tie between two persons, the tie between humans and chatbots can be strengthened by warm utterances from chatbots (Williams & Bartlett, 2015; Chuah & Yu, 2021). The reason for this similarity is that both humans and human-like chatbots have the ability to display emotions through communication (Benke et al., 2022), and displaying emotions facilitates the construction of emotional bonds (Rincon et al., 2019; Skjuve et al., 2021). Closeness or intimacy (also referred to as emotional bonds) is proven to be the

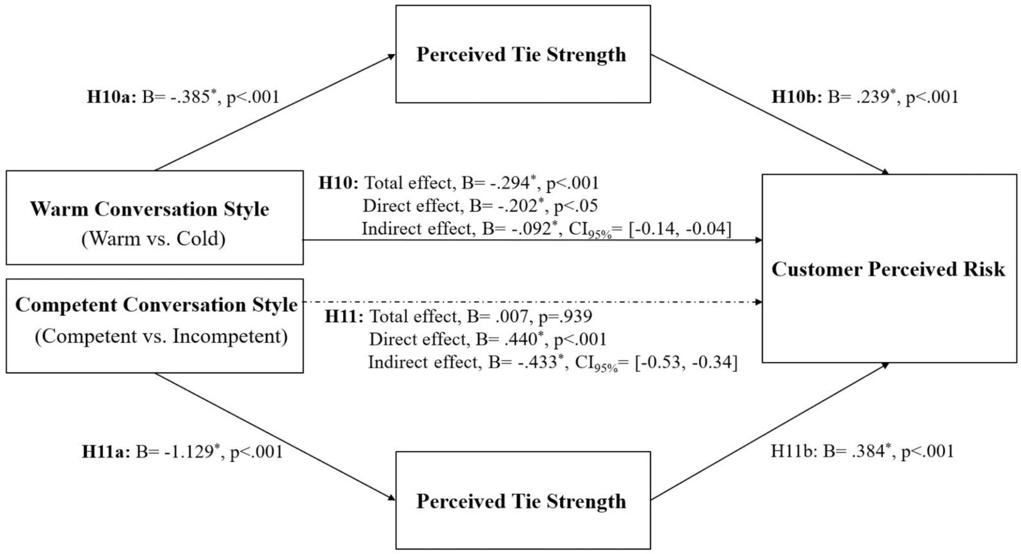

Figure 6. Mediation effects of perceived tie strength.

Table 10. The output of pairwise comparisons for perceived financial risk, perceived psychological risk, and perceived privacy risk.

	N	*M*	*SD*	$M_{difference}$	Sig.
Perceived financial risk					
Warm *vs.* cold conversation style					
Warm (I)	160	5.33[a]	.98	−.305* (I-J)	<.001
Cold (J)	160	5.64[a]	1.09	.305* (J-I)	<.001
Competent *vs.* incompetent conversation style					
Competent (I)	159	5.50[a]	1.00	.019 (I-J)	.832
Incompetent (J)	161	5.48[a]	1.10	−.019 (J-I)	.832
Perceived psychological risk					
Warm *vs.* cold conversation style					
Warm (I)	160	5.47[a]	.95	−.165 (I-J)	.069
Cold (J)	160	5.64[a]	1.08	.165 (J-I)	.069
Competent *vs.* incompetent conversation style					
Competent (I)	159	5.52[a]	0.97	−.073 (I-J)	.418
Incompetent (J)	161	5.59[a]	1.07	.073 (J-I)	.418
Perceived privacy risk					
Warm *vs.* cold conversation style					
Warm (I)	160	5.57[a]	.96	−.431* (I-J)	<.001
Cold (J)	160	6.00[a]	1.15	.431* (J-I)	<.001
Competent *vs.* incompetent conversation style					
Competent (I)	159	5.85[a]	1.08	.126 (I-J)	.160
Incompetent (J)	161	5.73[a]	1.09	−.126 (J-I)	.160

*The mean difference is significant at the .05 level.
[a]Covariates appearing in the model are evaluated at the following values: Risk aversion = 5.9090.

most influential construct for perceived tie strength not only by this study but also by other research (Stanko et al., 2007). A possible explanation is that chatbot anthropomorphism enhances the ability of chatbots to exhibit emotions through warm utterances, and emotions stimulate perceived closeness which plays an important role in lessening risk perception.

The establishment of buyer-seller relationships relies heavily on the competence of salespersons (Srinivasan et al., 2020). The findings strengthen the advocacy of Miklósi et al. (2017): when chatbots are endowed with social competence, humans finally interact with them independently of their embodiment. Even more, for tie strength, the impact of competence is higher than conversation warmth. So, the human–chatbot relationship which is similar to interpersonal relationships can be built by increasing conversation competence, and it is essential to assure the customers of the competence of the chatbot to strengthen the tie.

To conclude, the findings revealed the importance of perceived tie strength in the online shopping context. Unlike technology acceptance and risk perception, both warmth and competence play a role in tie strength. This finding supports the idea that chatbots are perceived as social entities rather than mere machines. Humans evaluate the bond with chatbots by considering both the social and cognitive dimensions, much as they would when interacting with another human. Therefore, any study about social and economic activities that include chatbots is likely to be biased if it fails to recognize the impact of chatbots on human social networks. As such, it is crucial to take into account the social nature of chatbot interactions when analyzing their effects on human behavior.

Table 11. Results of two-way ANOVA for perceived financial risk, perceived psychological risk, and perceived privacy risk.

Source	Dependent variable	Type III sum of squares	*df*	Mean square	*F*	Sig.	Partial eta-squared
Corrected model	Financial risk	142.583[a]	4	35.646	53.406	<.001	.404
	Psychological risk	126.263[b]	4	31.566	48.202	<.001	.380
	Privacy risk	173.001[c]	4	43.250	67.698	<.001	.462
Intercept	Financial risk	3.705	1	3.705	5.550	<.05	.017
	Psychological risk	5.403	1	5.403	8.251	<.05	.026
	Privacy risk	2.614	1	2.614	4.092	<.05	.013
Risk aversion	Financial risk	127.472	1	127.472	190.984	<.001	.377
	Psychological risk	122.246	1	122.246	186.675	<.001	.372
	Privacy risk	152.053	1	152.053	238.001	<.001	.430
Warm *vs.* cold	Financial risk	7.432	1	7.432	11.134	<.001	.034
	Psychological risk	2.174	1	2.174	3.320	.069	.010
	Privacy risk	14.835	1	14.835	23.220	<.001	.069
Competent *vs.* incompetent	Financial risk	.030	1	.030	.045	.832	.000
	Psychological risk	.430	1	.430	.656	.418	.002
	Privacy risk	1.268	1	1.268	1.985	.160	.006
Warm *vs.* cold * competent *vs.* incompetent	Financial risk	3.591	1	3.591	5.380	<.05	.017
	Psychological risk	.030	1	.030	.045	.832	.000
	Privacy risk	1.471	1	1.471	2.302	.130	.007
Error	Financial risk	210.247	315	.667			
	Psychological risk	206.280	315	.655			
	Privacy risk	201.245	315	.639			
Total	Financial risk	9985.222	320				
	Psychological risk	10,211.556	320				
	Privacy risk	11,096.556	320				
Corrected total	Financial risk	352.830	319				
	Psychological risk	332.543	319				
	Privacy risk	374.247	319				

$N = 320$.
Warm *vs.* cold * competent *vs.* incompetent refers to the interaction effects of the two conversation styles.
[a]R squared = .404 (adjusted R squared = .397).
[b]R squared = .380 (adjusted R squared = .372).
[c]R squared = .462 (adjusted R squared = .455).

Table 12. The output of pairwise comparisons for closeness, mutual confiding, and reciprocity.

	N	*M*	*SD*	$M_{difference}$	Sig.
Closeness					
Warm *vs.* cold conversation style					
Warm (I)	160	3.68	.98	1.359* (I-J)	<.001
Cold (J)	160	2.32	1.09	−1.359* (J-I)	<.001
Competent *vs.* incompetent conversation style					
Competent (I)	159	3.99	1.00	1.969* (I-J)	<.001
Incompetent (J)	161	2.02	1.10	−1.969* (J-I)	<.001
Mutual confiding					
Warm *vs.* cold conversation style					
Warm (I)	160	3.93	.95	.283* (I-J)	<.05
Cold (J)	160	3.64	1.08	−.283* (J-I)	<.05
Competent *vs.* incompetent conversation style					
Competent (I)	159	4.42	0.97	1.271* (I-J)	<.001
Incompetent (J)	161	3.15	1.07	−1.271* (J-I)	<.001
Reciprocity					
Warm *vs.* cold conversation style					
Warm (I)	160	4.12	.96	.094 (I-J)	.511
Cold (J)	160	4.03	1.15	−.094 (J-I)	.511
Competent *vs.* incompetent conversation style					
Competent (I)	159	4.92	1.08	1.271* (I-J)	<.001
Incompetent (J)	161	3.23	1.09	−1.271* (J-I)	<.001

*The mean difference is significant at the .05 level.

5.4. Theoretical contribution

First, this article enriches current literature regarding AI anthropomorphism in business by focusing on the internal psychological mechanisms of customers. Before purchase intention and decision-making, the psychological state and subliminal cognitive processes of the customers can be manipulated by changing the conversation style of chatbots. Specifically, compared with competence, chatbot warmth plays a more positive role in manipulating customer cognitive processes.

Secondly, this article expands the application of the RET framework, previously limited to human-to-human interactions (Panagopoulos et al., 2017; Shen et al., 2016; Stanko et al., 2007; Umashankar et al., 2017), to a broader context. AI's pervasive adoption is increasingly evident in our socioeconomic activities, where it has assumed a diverse range of roles that were previously fulfilled exclusively by humans.

Table 13. Results of two-way ANOVA for closeness, mutual confiding, and reciprocity.

Source	Dependent variable	Type III sum of squares	*df*	Mean square	*F*	Sig.	Partial eta-squared
Corrected model	Closeness	476.258[a]	3	158.753	82.259	<.001	.438
	Mutual confiding	157.475[b]	3	52.492	37.183	<.001	.261
	Reciprocity	244.460[c]	3	81.487	49.958	<.001	.322
Intercept	Closeness	2882.874	1	2882.874	1493.790	<.001	.825
	Mutual confiding	4580.624	1	4580.624	3244.727	<.001	.911
	Reciprocity	5310.369	1	5310.369	3255.710	<.001	.912
Warm *vs.* cold	Closeness	147.798	1	147.798	76.583	<.001	.195
	Mutual confiding	6.398	1	6.398	4.532	<.05	.014
	Reciprocity	.707	1	.707	.433	.511	.001
Competent *vs.* incompetent	Closeness	310.009	1	310.009	160.634	<.001	.337
	Mutual confiding	129.129	1	129.129	91.470	<.001	.224
	Reciprocity	230.707	1	230.707	141.443	<.001	.309
Warm *vs.* cold * competent *vs.* incompetent	Closeness	16.359	1	16.359	8.477	<.05	.026
	Mutual confiding	21.725	1	21.725	15.389	<.001	.046
	Reciprocity	12.911	1	12.911	7.916	<.05	.024
Error	Closeness	609.850	316	1.930			
	Mutual confiding	446.101	316	1.412			
	Reciprocity	515.426	316	1.631			
Total	Closeness	3960.111	320				
	Mutual confiding	5178.889	320				
	Reciprocity	6060.111	320				
Corrected total	Closeness	1086.108	319				
	Mutual confiding	603.576	319				
	Reciprocity	759.886	319				

$N = 320$.
Warm *vs.* cold * competent *vs.* incompetent refers to the interaction effects of the two conversation styles.
[a] R squared = .438 (adjusted R squared = .433).
[b] R squared = .261 (adjusted R squared = .254).
[c] R squared = .322 (adjusted R squared = .315).

The social presence of anthropomorphic chatbots is confirmed by Adam et al. (2020), meanwhile, a parasocial interaction exists between customers and human-like chatbots (Youn & Jin, 2021). This article makes a contribution by showing that social relationships can be also built between humans and chatbots under the frame of RET. More importantly, this article opens a door to human–chatbot relationship management and reminds future researchers not to simply regard chatbots as non-human entities, especially when it comes to socio-economic activities.

Lastly, this study is one of the first in the literature to combine the affection (warmth) and capability (competence) of chatbots into a social psychology theory (Relational Embeddedness Theory) and an information systems theory (Technology Acceptance Model), providing an opportunity to reflect on how do people's cognition, psychological state, and social networks change with the evolution of chatbots from simple conversation agents to human-level roles.

5.5. Managerial implication

The research also has some managerial implications for designers and marketers. First, to reduce customer-perceived risk, especially financial and privacy risks, managers are encouraged to design chatbots to be more friendly, kind, and enthusiastic. Second, enhancing communication competence rather than warmth can increase customers' intention to use chatbots and thus save the cost of human services. So, conversation warmth and competence should be adjusted to different degrees for different purposes. More importantly, customer relationship management can be extended to customer chatbot relationships and can be optimized by adjusting conversation warmth and competence.

6. Limitations and future research

The study has several limitations which have great potential for future research. First, some risk factors, such as social and time risks are also meaningful to discover. They can provide practitioners with more comprehensive and specific insights to manipulate customer risk perception. Second, because most participants are university students and the experiment product is a smartphone, the relatively fixed sample age, educational level, prior experience, and product category help the experiment to be conducted in a controlled condition. On the other hand, it forms a very homogenous group which makes it hard to generalize. Therefore, the research can be expanded to more diversified groups and contexts. Third, chatbot transparency is an important factor in customer risk perception, and it can be interesting to dive deeper into whether pre-disclosure of chatbot identity leads to different degrees of risk perception. Fourth, the study fails to uncover the influence of anthropomorphism on technology use intention. Song and Shin (2022) studied the effects of anthropomorphism on user's trust, and the mediating effect of trust in pathways between anthropomorphism, purchase intention, and willingness to reuse while Jin and Youn (2023) found that continuance intention can be predicted by anthropomorphism. Given the influence of trust on perceived risk (Mortimer et al., 2016), the study can be enhanced by new dimensions, such as trust and usage intentions. Fifth, TAM has been updated with TAM3 and the study is open to be reconducted utilizing TAM3 as a way to measure the effectiveness of the newly introduced dimensions. Sixth, anthropomorphism is conveyed through communicational and visual cues (emoticons) in the experiments, but their interaction effect is not taken into account. Furthermore, the conversation style of chatbots represents only one of several potential tools for controlling their anthropomorphism. Future research should explore additional tools, such as variations in voice and appearance to further enrich the theoretical framework. Finally, participants are asked to answer the survey questions based on the screenshots. Even though this method has been utilized in the literature as a way to assess people's opinions, letting the participants engage with the chatbots in future research would allow them to answer based on their own experiences.

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Appendix A: English and Chinese screenshots for each condition

Figure A1. Warm and competent.

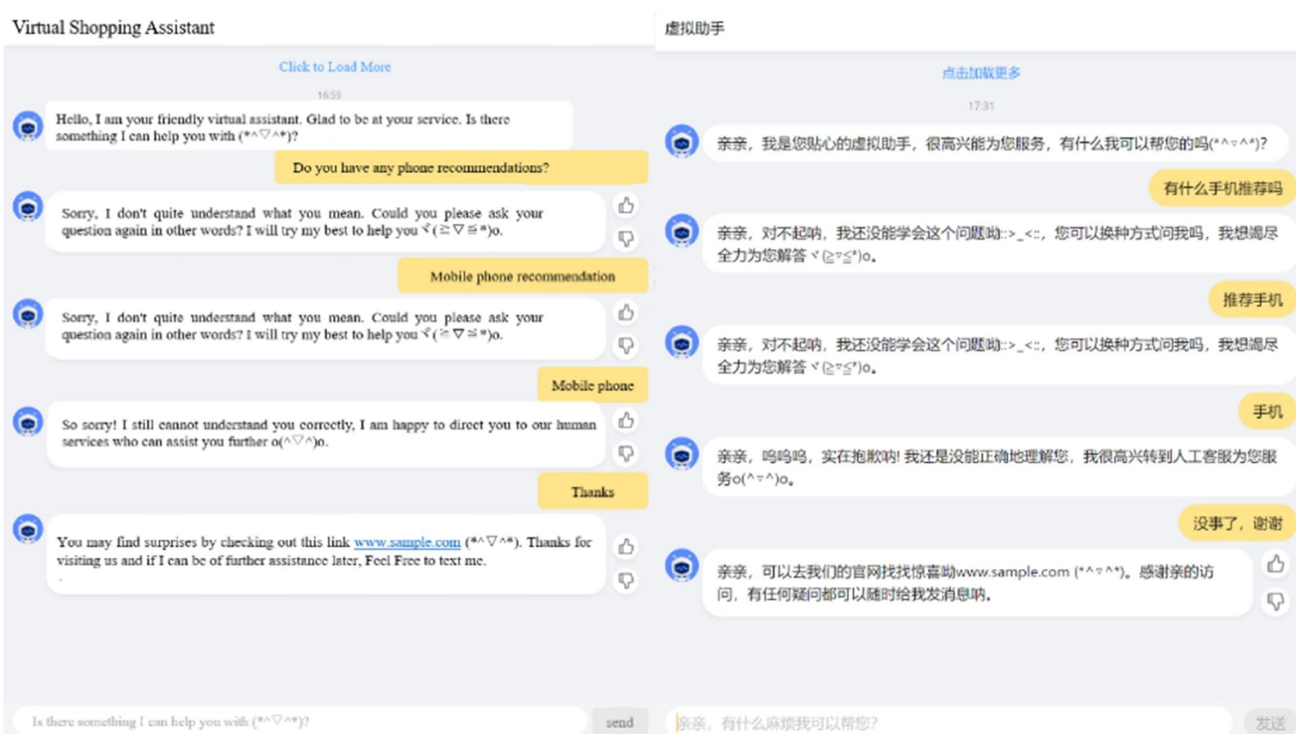

Figure A2. Warm and incompetent.

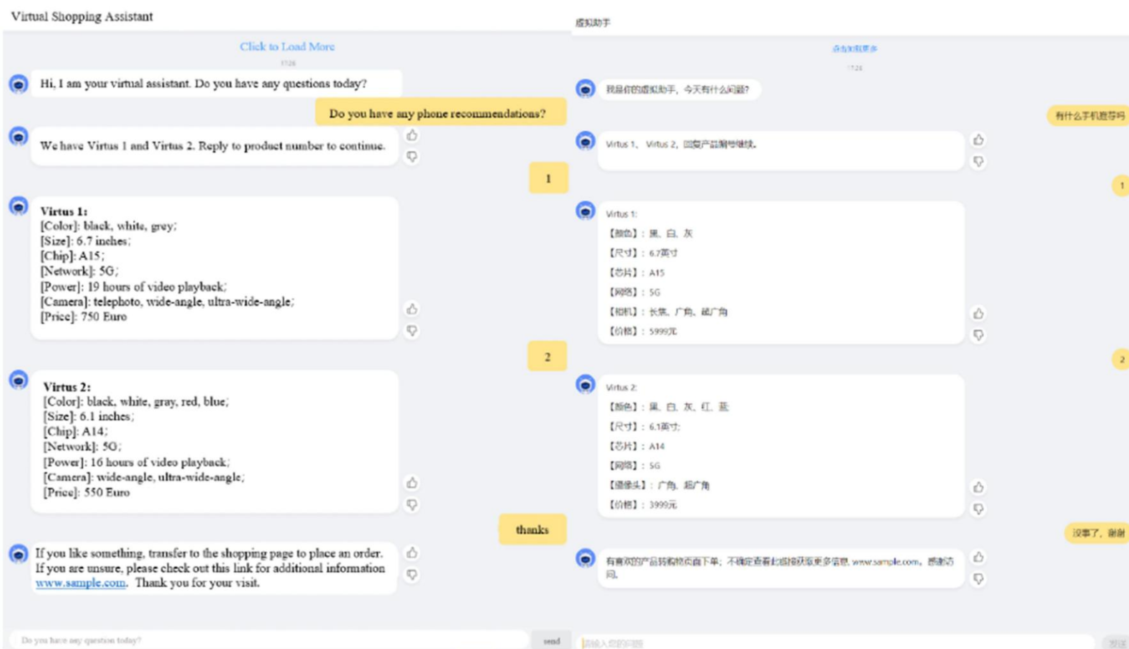

Figure A3. Cold and competent.

Figure A4. Cold and incompetent.

Appendix B: Manipulation check questions and statistics during pretest

Scale	*M*	*SD*	Cronbach's α
Warm conversation style	4.32	1.46	.989
– The chatbot is warm during communication.			
– The chatbot is friendly during communication.			
– The chatbot is kind during communication.			
– The chatbot is enthusiastic during communication.			
Competent conversation style	3.84	2.43	.927
– The chatbot is competent during communication.			
– The chatbot is capable of communication.			
– The chatbot is effective during communication.			
– The chatbot is intelligent during communication.			

Note: N = 320.

Appendix C: Items for all variables and reliability test results during pretest

Scale	*M*	*SD*	Cronbach's α	KMO
Customer perceived risk	5.49	1.03	.950	.879
Performance risk (PerR)				
– I would be concerned that the product recommended by the chatbot may not match the descriptions or pictures given on the website.				
– I would be concerned that the product recommended by the chatbot may have some quality problems.				
Financial risk (FR)				
– I would be concerned that the price of the product recommended by the chatbot may be too high.				
– I would be concerned that the product recommended by the chatbot may have a low cost-performance ratio.				
– I would be concerned that I may suffer from extra monetary loss due to the chatbot's fraudulent acts.				
Psychological risk (PsyR)				
– I may feel anxious about buying the product recommended by the chatbot.				
– I may feel unpleasant if the product recommended by the chatbot doesn't meet my expectations.				
– I may feel pressured if the product recommended by the chatbot has quality problems.				
Privacy risk (PriR)				
– I would be concerned that personal information associated with shopping through the chatbot can be misused.				
– I would be concerned that personal information associated with shopping through the chatbot can be used in a way I cannot foresee.				
– I would be concerned that there is too much uncertainty about personal information associated with shopping through the chatbot.				
Chatbot acceptance	4.04	1.97	.953	.891
Perceived usefulness (PU)				
– I find the chatbot to be useful for shopping.				
– I can get clear product information effectively with the chatbot.				
– I can accomplish shopping tasks productively with the chatbot.				
Perceived ease-of-use (PEOU)				
– I find the chatbot to be easy to use for shopping.				
– I can operate the chatbots to shop without the help of others.				
– I can easily understand what is going on; Working with chatbots is not complicated.				
Perceived tie strength	3.62	1.46	.945	.889
Closeness/emotional intensity (C)				
– I feel close to the chatbot.				
– I enjoy interacting with the chatbot.				
– I have a virtual friendship with the chatbot.				
Mutual confiding (MC)				
– I am willing to keep the chatbot informed of my needs in detail.				
– I am willing to share reasons with the chatbot why I plan to buy a product.				
– I am willing to share private personal information with the chatbot.				

(*continued*)

Continued.

Scale	*M*	*SD*	Cronbach's α	KMO
Reciprocity (R)				
– I am willing to paraphrase my questions as a payback for the chatbot's efforts to help me.				
– I am willing to learn more about a product recommended by the chatbot as a payback for the chatbot's efforts to help me.				
– I am willing to buy a product recommended by the chatbot as a payback for the chatbot's efforts to help me.				
Risk aversion	5.91	.80	.929	.768
– When I shop online, I would like to seek unbiased information sources.				
– When I shop online, I would like to look for a money-back guarantee.				
– When I shop online, I would like to go for one that I have seen others using.				

Note: N = 320.