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Customer experience quality with social robots: Does trust matter?

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ABSTRACT

Although service providers increasingly adopt social robots, much remains to be learned about what influences customers' experiences with robots. To address this issue, this study investigates the relationships among customer equity drivers (i.e., value equity, brand equity and relationship equity), trust in social robots, and trust in service providers. Specifically, we hypothesize that customer equity drivers influence trust in social robots and trust in service providers. We also propose that customer equity drivers influence customer experience quality in the context of social robots and that trust in social robots and trust in service providers mediate these relationships. The study used a two-stage hybrid partial least squares structural equation modelling (PLS-SEM)-artificial neural network (ANN) analysis to examine the proposed relationships. Findings show that while all the customer equity drivers influence trust in service providers, only brand and relationship equity influence trust in social robots. Results also suggest that trust in service providers mediates the relationship between customer equity drivers and customer experience quality. In addition, we find that consumers' trust in service providers helps generate trust in social robots. Theoretical and managerial implications are discussed.

1. Introduction

His name is Furhat and he might just be among the most advanced humanoid social robots out there. In a retail context, he has the potential to access online orders, automate in-store pickup processes, answer customer questions, collect feedback, and help managers monitor inventory (Furhat Robotics, 2021). It might not come as a surprise then that retail adoption of social robots is expected to gain further momentum, with an international robotics market expected to grow from just under USD 2 to 11.24 billion by the end of 2026 (Business Wire, 2023). In parallel, the services literature on social robots and their operating systems/artificial intelligence is mushrooming (e.g., Borghi and Mariani, 2022; Park et al., 2021).

The increasing prevalence of social robots in retail is consistent with Industry 5.0 tenets, which advocate for "humans and machines acting synergistically" (Haesevoets et al., 2021, p. 2). The basic idea here is simple: technology should augment, not substitute, those working in the services industry with flow-on benefits for customers (Noble et al., 2022). Indeed, social robots have been shown to act as (1) entertainers, (2) social enablers, (3) friends, and (4) mentors to customers (Henkel et al., 2020), which suggests that robots can be perceived as supportive, emotional, and hence *social* actors (De Graaf et al., 2015). Social robots can perform many functions and roles with transformative potential when orchestrating customer experiences. For example, social robots have proven effective in handling repetitive tasks, like transporting objects and the execution of monotonous assembly jobs (Lu et al., 2020). More recently, they have shown that they can perform complex physical and cognitive assignments, such as identifying signs of worsening dementia in patients (Lay, 2019). Also, social robots are finding increasingly advanced applications in professional domains, such as assisting in financial auditing and even aiding in surgical procedures through voice-activated robotic arms (Barrett et al., 2012). These advancements enable service providers to scale their offerings, enhance their productivity, reduce operational expenses, and automate service processes, among other benefits (Wirtz et al., 2023).

Service providers place high-quality customer experience at the core of their offering, mainly when social robots enhance in-store customer services (Lu et al., 2020). Why, then, do several reports highlight just how unhappy customers are with social robots (Puntoni et al., 2021; Liu-Thompkins et al., 2022)? For example, a study of Facebook users shows

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that most users (~70 %) prefer human interaction (Song et al., 2022) because they are dissatisfied with the quality of interactions they have had with social robots (Jörling et al., 2019). Against this backdrop, much remains unknown about how to use social robots to improve customers' retail experiences. To address this issue, we explore customer experience quality drivers with social robots in the retailing context in this study.

This critical problem of ensuring customer experience quality has caught the attention of academic scholars. With most of the literature focused on conceptualizing experience quality and its nomological network (e.g., Puntoni et al., 2021; Liu-Thompkins et al., 2022), empirical research on the factors enabling experience quality with social robots is relatively scant. To address this gap, we provide a comprehensive research model to examine experience quality with social robots in retailing through customer equity drivers (i.e., value equity, brand equity, and relationship equity) (Rust et al., 2001). In addition, according to relationship marketing theory, trust serves as a bridge between service and relational outcomes (Morgan and Hunt, 1994); therefore, we integrated customers' perceived trust in social robots and perceived trust in the service provider as factors mediating the relationship between equity drivers and experience quality (Bawack et al., 2021; Lankton et al., 2015). Specifically, we intend to explore whether trust in social robots and trust in service providers affect customer equity drivers and experience quality (Ameen et al., 2021; Kim et al., 2022).

In summary, this study has two research questions:

1. Explored through the lens of customer equity drivers, what factors determine customer experience quality with social robots?
2. How do trust in social robots and trust in service providers influence the relationship between customer equity drivers and customer experience quality with social robots?

To address these questions, we use a PLS-SEM-ANN approach. PLS-SEM examines linear hypothesized relationships and ANN captures non-linear relationships (Wang et al., 2022). The data were collected through a survey based on the use of a prototypical humanoid robot (i.e., social robot). Using the hybrid PLS-SEM-ANN approach, this is one of the first studies to capture the complex relationships among customer experience quality and trusts in service provider and social robots.

Our study makes several key contributions. First, we find that three customer equity drivers influence trust in service providers (Ramaseshan et al., 2013) but only brand equity and relationship equity influence trust in social robots. Second, we reveal the essential aspects of the process that drives customer experience quality in social robots backed retail. Specifically, we find that critical relational variables such as trust in service providers mediate the relationship between all customer equity drivers and experience quality. However, trust in social robots mediates the relationship between two customer equity drivers (i.e., brand equity and relationship equity) and customer experience quality, but not the value equity-customer experience quality relationship. This finding extends previous studies that have found the direct relationship between customer equity drivers and customer experience quality (Gao et al., 2020). Third, we find that trust in service providers also contributes to developing trust in social robots. Finally, results show that customer experience quality with social robots depends on consumers' trust in both the service providers and the robots. Overall, we tackle real-world questions, for example, in what ways service providers can enhance the quality of customer experiences in a retail environment supported by social robots (Grewal et al., 2020).

The following section presents the theoretical underpinnings of our proposed research model. Next, the research methodology, data collection and data analysis are described. The paper concludes with a discussion and study implications.

2. Research model

A research model is proposed to examine the drivers of customers' experience quality with social robots in the retailing context. We theoretically ground this research model in the customer equity framework of Rust et al. (2001) and Rust et al. (2004). By examining the three customer equity drivers, namely, value equity, brand equity, and relationship equity, we select some of the critical drivers suggested by the literature (Gao et al., 2020). Further, building on relationship marketing theory, we integrate trust in social robots and trust in service providers in our research model, which recognizes that trust also influences customer experience quality (e.g., Bawack et al., 2021). Indeed, perceived trust in service providers and trust in social robots are key factors that potentially influence customer experience quality. Fig. 1 illustrates our proposed research model.

2.1. *Customer experience quality*

Broadly speaking, customer experiences are "non-deliberate, spontaneous responses and reactions to particular stimuli" (Becker and Jaakkola, 2020, p 637). In our research, customer experience develops through interactions with a service provider and a social robot (De Keyser et al., 2020). The individuals' perceptions about the quality of their experience may vary depending on their judgments about the excellence or superiority of interaction with stimuli. Consistent with that, we adopt the definition of customer experience quality as "perceived judgment about the excellence or superiority of the customer experience" as it is considered a superior construct and better evaluation metric (Lemke et al., 2011 p. 848).

2.2. *Customer equity drivers*

Rust et al. (2004) conceptualized the customer equity framework to examine the influence of marketing activities on consumer behavior. Specifically, they defined firms' investments in three core areas—value equity, brand equity and relationship equity—and their corresponding influence on consumers. The research hypotheses section describes each of the three equity drivers.

2.3. *Trust in social robots*

Customer trust refers to the attitude or belief that the social robot can assist consumers in fulfilling the goals they intend to achieve (Tussyadiah et al., 2020). We follow McKnight et al. (2011) theorization to adapt trust in social robots based on social robots' reliability, functionality, and helpfulness. Reliability refers to the belief that social robots consistently deliver the service accurately. Functionality represents that social robots have been configured to skilfully handle the service delivery. Helpfulness highlights that social robots provide adequate and responsive assistance to users during service interaction (McKnight et al., 2011).

2.4. *Trust in service provider*

Consumers' trust in service providers comprises two key components: cognitive trust and affective trust (Johnson and Grayson, 2005). Cognitive trust is driven by the knowledge that evaluates the service provider's competence and reliability in handling the service interactions (Moorman et al., 1993). Whereas affective trust is driven by emotions generated during interactions with service providers (Rempel et al., 1985).

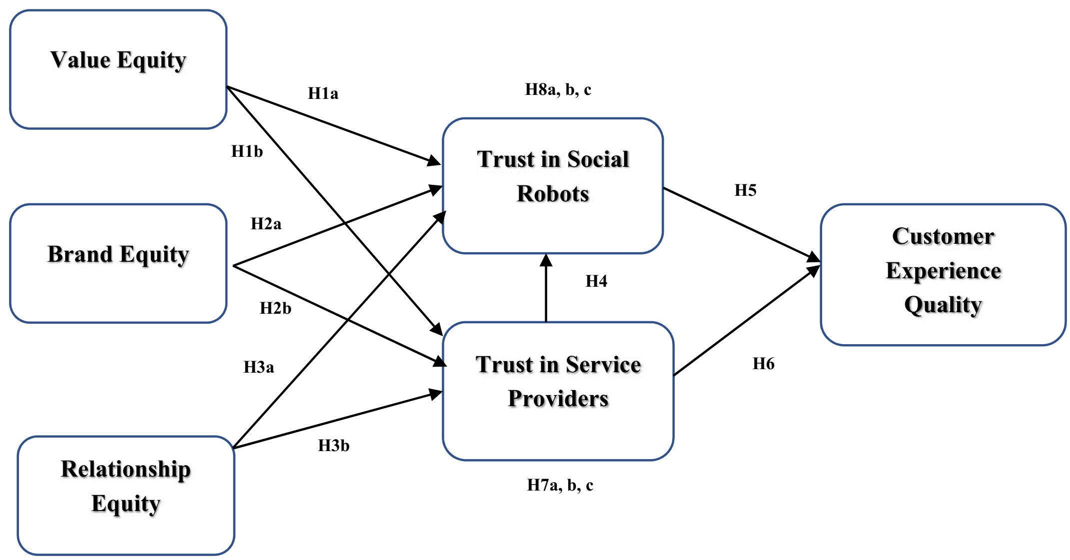


Fig. 1. Research model.

3. Research hypotheses

3.1. Customer equity drivers, trust in social robots and trust in service providers

Value equity indicates the customer's evaluation of a brand's utility (Rust et al., 2001; Ou et al., 2017). It is the perceived ratio between tangible/intangible benefits and monetary/non-monetary costs, and thus a higher cost-benefit ratio will generate higher value equity.

An effective and efficient customer service creates value equity. The presence of social robots for service delivery results in greater perceptions of service quality in terms of efficiency and effectiveness, thereby increasing customers' perceived value equity (Wirtz, 2019). Further, the value provided by social robots invokes trust between customers and social robots (Čaić et al., 2019). Therefore, investing in value equity generates more trust, which can change customers' dispositions towards, and interaction with, service providers (Ryssel et al., 2004). Based on the preceding discussion and consistent with the literature (e.g., Ramaseshan et al., 2013), we advance the following:

H1. Value equity has a positive impact on (a) trust in social robots and (b) trust in service providers.

Brand equity represents a more subjective and emotional appraisal of the brand beyond its perceived objective value (Vogel et al., 2008; Richards and Jones, 2008). Brand awareness drives brand equity (Richards and Jones, 2008). Apart from functional purposes, the infusion of social robots by the service provider responds to their requirements for branding strategies, including the need to promote their brand awareness (Aymerich-Franch and Ferrer, 2020). Hence, when a service provider invests in social robots, it provides added value to customers in comparison to a retail setting without social robots, ultimately leading to the establishment of trust among customers (Ramaseshan et al., 2013). We posit that greater trust can be generated by investing efforts in brand equity. Hence, we propose the following:

H2. Brand equity has a positive impact on (a) trust in social robots and (b) trust in service providers.

Apart from value and brand equity, relationship equity further strengthens the relationship between customers and the brand. Rust et al. (2005) define relationship equity as the customers' tendency to remain loyal to the service provider based on evaluations beyond objective and subjective factors. In human-robot interactions, a successful interaction acts as the foundation of a (long-term) relationship, with every subsequent successful interaction generating greater trust between the parties. A series of flawless transactions ultimately leads to a situation or a state of inertia where customers look forward to interacting with the social robots (Gounaris and Venetis, 2002). This implies that investing in relationship equity can generate more trust in social robots. Thus, it is anticipated that relationship equity will influence trust in service providers and trust in social robots. Therefore, we advance the following hypothesis:

H3. Relationship equity has a positive impact on (a) trust in social robots and (b) trust in service providers.

3.2. Trust in service providers and trust in social robots

When social robots are used to deliver customer service with or without human involvement, it is highly likely that, at first, consumers may perceive some uncertainty about robots' ability to effectively deliver customer service (Pavlou, 2003). One way to reduce uncertainty is by developing trust in service providers and promoting safety in a transaction (Collier and Sherrell, 2010). Therefore, creating trust is a core priority in situations where uncertainty prevails. Pavlou (2003) proposed that customer trust depends on two parameters, i.e., the characteristics of the service provider and technologies infused by the service provider. Service providers can generate/enhance customers' trust in the technology by facilitating encrypted transactions, using authentication mechanisms, and ensuring privacy (Cassell and Bickmore, 2000). Therefore, technological uncertainty can be strongly influenced by the behavioral actions of service providers and eventually increase trust in social robots. Therefore, we hypothesize that:

H4. Trust in service providers positively impacts trust in social robots.

3.3. Trust in social robots, trust in service providers and customer experience quality

The literature on trusting technology-mediated services puts forth two main dimensions: trust in technology and trust in the service providers (Ghazizadeh et al., 2012; Nienaber and Schewe, 2014). These two dimensions imply that trusting the service provider and the social robot is essential in technology-enabled service settings (Corritore et al., 2003). Service providers often presume that the infusion of technologies, including social robots, is sufficient to delight customers. Yet, many studies show that this is short-sighted if service providers fail to address technological and/or behavioral concerns related to technology

(Heidenreich and Spieth, 2013) and highlight the importance of developing trust in the service provider and their intent to use new-age technologies including social robots (Park, 2020). Unlike in other e-commerce shopping mediums, where the intentions and processes are predefined, AI-based social robots are expected to learn, understand, adapt, and evolve following individual customer data (Haenlein and Kaplan, 2019). Thus, customers using social robots for service delivery can be reasonably expected to trust that their data will not be misused by the service providers and their technology (i.e., social robot). Consequently, trust in the service providers could play a vital role in the perceived quality of customer experience, and, in turn, help build trust in social robots (Park, 2020).

Prior studies show that a higher level of trust in service providers and trust in social robots improves customers' experience (Ameen et al., 2021). Further, it can be argued that trust has a relationship with customer experience as trust can help reduce the required cognitive effort when customers access services using a social robot (Lemon and Verhoef, 2016; Huang et al., 2021). Therefore, we hypothesize that:

H5. Trust in social robots has a positive impact on customer experience quality with social robots.

H6. Trust in service providers positively impacts customer experience quality with social robots.

3.4. Mediating effects of trust in service providers and trust in social robots

In the proposed model, customer equity drivers influence customer experience quality linked with social robots (see Fig. 1). We suggest that this relationship is mediated by trust in service providers and trust in social robots. Prior research has investigated the direct impact of customer equity drivers on experience quality (Gao et al., 2020). The arguments for the direct effects of customer equity drivers on customer experience quality are persuasive. However, we propose that this relationship between customer equity drivers and customer experience quality is implicitly linked through trust (Ramaseshan et al., 2013; Ameen et al., 2021; Kim et al., 2022). Specifically, we propose that the relationship between customer equity drivers and customer experience quality is mediated by trust in service providers and trust in social robots. This is because it is neither the customer's objective, subjective or relationship evaluation but their trust in the service provider and their trust in technology (social robot) that impacts the quality of their experience. Specifically, trust in service providers and trust in social robots ensures customer experience quality because it enhances the likelihood of quality interactions with customers. Implicit in this argument is the notion that trust in social robots and trust in service providers connect customer perceptions about the company's investments in equity drivers and their experience. Therefore, we hypothesize that:

H7. Trust in service providers mediates the relationship between (a) value equity, (b) brand equity, (c) relationship equity and customer experience quality.

H8. Trust in social robots mediates the relationship between (a) value equity, (b) brand equity, (c) relationship equity and customer experience quality.

4. Methodology

4.1. Questionnaire and data collection

This research was conducted in Australia. A prototypical humanoid robot in a video stimulus was adopted and shown to the participants for methodological rigor, offering them an accurate description of the phenomenon of social robots and achieving a valid survey response (see Appendix A). A literature review highlights that a humanoid robot is a widely accepted example of a social robot used across different service settings. Therefore, we embraced the humanoid robot to understand the nuances of human-robot interactions.

The data were collected using a Mechanical Turk (MTurk) survey. We targeted only those participants with prior experience of interacting with social robots in the retailing context. While setting up MTurk, we implemented recommended actions such as (a) offering adequate remuneration (i.e., $2) to encourage respondents to participate and provide accurate responses, (b) paying every participant even if the responses were not used, (c) pilot-testing the questionnaire ($n = 30$) and (d) setting the approval rate at 95 % or higher (Aguinis et al., 2021; Goodman and Paolacci, 2017). The survey opened with a textual description of social robots, followed by humanoid robots and video stimuli, respectively (Appendix A). The seven-point scale (1–7) was used to measure all items, with 7 highlighting strongly agree and 1 representing strongly disagree. The study employed a minimum sample size based on Hair et al.'s (2012) guideline that the maximum-paths to any dependent variable should be multiplied by ten. Among the 326 respondents, the sample consists of more males (60 %) than females (40 %).

4.2. Measurement items

The validated measurement items were extracted from the previous literature (Table 1). The adapted measurement items corresponding to each construct and related sources are detailed in Table 1.

5. Data analysis

5.1. PLS structural equation modelling (PLS-SEM)

PLS-SEM with SmartPLS 3.0 (Ringle et al., 2015) was used in this study. PLS-SEM was used for data analysis since it can predict models using small sample sizes (Hair et al., 2012; Sarstedt et al., 2021). Further, PLS-SEM has better statistical power than covariance-based structural equation modelling (Sarstedt et al., 2017), making it ideal for prediction purposes and maintaining interpretability (Henseler, 2018). In PLS-SEM, the data were analyzed in two stages (Becker et al., 2012): (a) measurement properties of the constructs were evaluated, and (b) proposed hypotheses in the structural model were tested (Sarstedt et al., 2022).

5.2. Artificial neural network (ANN)

Studies that adopt a hybrid approach to compare the results of PLS-SEM and ANN have thrived recently (e.g., Ferasso and Alnoor, 2022). Whereas SEM is used to investigate linear hypothesized relationships, ANN is used to capture non-linear relationships (Wang et al., 2022). Therefore, a hybrid PLS-SEM-ANN approach (i.e., combining ANN with PLS-SEM) was used to unveil the complex linear and non-linear relationships that exist between the dependent and the independent variables (Leong et al., 2020; Priyadarshinee et al., 2017; Roy et al., 2017).

We adopted a dual-stage or hybrid approach, whereby, in the first stage, the stated hypothesis was first tested using PLS-SEM and then, in the second stage, the significant relationships obtained from PLS-SEM were used as the inputs for the ANN analysis (Chong, 2013; Leong et al., 2020; Liébana-Cabanillas et al., 2018). This second stage attempts to capture non-linear relationships not evident from the SEM analysis.

Further, ANN analysis is used to determine the relative importance of the predictor constructs and then compare with the results obtained from the PLS-SEM approach (Şehrïbanoğlu et al., 2022; Talukder et al., 2020; Wang et al., 2022). The sigmoid function (Fig. 2[1]) was used as the activation function to generate the relationships among the ANN layers

[1] Source: https://www.linkedin.com/pulse/logistic-regression-sigmoid-function-explained-plain-english-hsu/.

Table 1
Measurement items.

Construct	Source	Measurement items
Customer Experience Quality	Gao et al., 2020	It is a pleasure for me to shop at this service provider (retailer) (CEQ1) I feel comfortable when I interact with this service provider (retailer) (CEQ2) This service provider (retailer) meets my needs and covers my expectations (CEQ3) I like to interact with this service provider (retailer) (CEQ4) I feel like this service provider (retailer) cares about keeping me as a customer (CEQ5) Please value the quality of the relationship with this service provider (retailer) (CEQ6)
Relationship Equity	Gao et al., 2020; Vogel et al., 2008	I have trust in this service provider (retailer) for hiring a robot (pepper) to deliver customer service (RE1) I feel this service provider (retailer) is close to me (RE2) I think this service provider (retailer) makes several investments to improve our relationship (RE3) I perceive that this service provider (retailer) tries to improve our relationship (RE4)
Brand Equity	Gao et al., 2020	I pay a lot of attention to everything about this service provider (retailer) (BE1) Everything related to this service provider (retailer) grabs my interest (BE2) I identify myself with the values that this service provider (retailer) represents to me (BE3)
Value Equity	Gao et al., 2020	I stay with this service provider (retailer) because both (this retailer and I) can benefit from this (VE1) I want to keep shopping at this service provider (retailer) because it is difficult to find another retailer like this (VE2) I am happy with the services received from this service provider (retailer) (VE3)
Trust in Service Providers	Ennew and Sekhon, 2007	This service provider (retailer) is honest with its customers (TSP1) This service provider (retailer)is very reliable (TSP2) This service provider (retailer)is very responsible (TSP3) This service provider (retailer) acts with good intentions (TSP4)
Trust in Social Robots	Park et al., 2021	I believe this robot hired by the service provider (retailer) can be trusted (TSR1) I believe this robot hired by the service provider (retailer) can be relied on to keep its promises (TSR2)

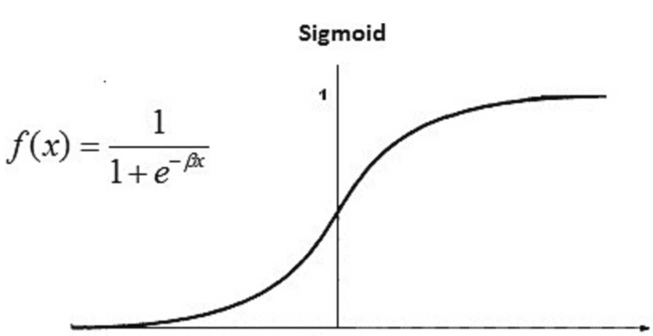


Fig. 2. The Sigmoid function.

using SPSS 26.0 version (Leong et al., 2020; Hew and Kadir, 2016). The sigmoid function can convert any real number within a range of 0 and 1, allowing for the capture of non-linearity (Ferasso and Alnoor, 2022; Leong et al., 2020). In addition, to minimize over-fitting problems, the ANN approach employs a 10-fold cross-validation technique. To assess the accuracy of the ANN results, the current dataset was split into 90 % training and 10 % testing sample datasets (Leong et al., 2020; Talukder et al., 2020; Wang et al., 2022).

6. Results

6.1. Common method bias

Based on the suggestions of Podsakoff et al. (2012), we used both procedural and statistical procedures to test for common method bias. We ensured that participant anonymity was maintained and requested the respondents to answer the survey questions honestly (MacKenzie and Podsakoff, 2012). In addition, we designed the questionnaire so that causal relationships between the independent and dependent variables were not self-evident. We also conducted an exploratory factor analysis, resulting in all measurement items loading onto their corresponding latent constructs. Based on the suggestions of Lindell and Whitney (2001), we used the marker variable method to examine common method bias. We chose respondents' mobile phone usage intensity as the marker variable (Valenzuela et al., 2009). A three-item scale was used to measure the marker variable. When we introduced this marker variable in the analysis, the variance in the dependent variable did not increase significantly. Results show that the average correlation between the latent construct and the marker variable is 0.035. Results also showed that the average significance value was 0.55, higher than the cut-off value 0.05. Thus, it can be concluded that common method bias is not a critical problem in this study.

6.2. PLS-SEM analysis

6.2.1. Measurement properties

The measurement properties of the research model are shown in Table 2. Items measuring the latent constructs loaded significantly onto the corresponding latent constructs. The respective factor loadings are all higher than 0.7 with statistically significant t-values (Henseler et al., 2015). The reliability and validity of the measurement model were examined using Cronbach's alpha, composite reliability and average variance extracted. The Cronbach's alpha for all the constructs exceeds the threshold value 0.70. Composite reliabilities of all the constructs exceeded the cut-off value of 0.70. These indicate the reliability of the measurement model (Hair et al., 2012). We assessed the convergent validity using the factor loadings and average variance extracted (AVE). All factor loadings were >0.5, and the AVE values were >0.5, too, indicating that the measurement model has convergent validity (Sarstedt et al., 2021). Table 3 shows that the latent constructs' AVE exceeded the inter-construct correlation square. Thus, the measurement model possesses discriminant validity (Fornell and Larcker, 1981). We also used the heterotrait-monotrait ratio (HTMT) to provide additional support for the discriminant validity of the measurement model. The HTMT ratios of all the constructs are <0.85 (Henseler et al., 2015), which shows that the measurement model possesses discriminant validity.

6.2.2. Structural model

We estimated the proposed hypothesis using 5000 bootstrapped resamples based on 326 cases to generate t-values. The predictive relevance of the research model was examined using the R^2 values and Stone-Geisser's Q^2 values (Hair et al., 2017). Results show that the R^2 value of the ultimate dependent variable (i.e., customers' experience quality) is 0.40, which is acceptable (Hair et al., 2017). R-square values for other endogenous variables, such as trust in service providers ($R^2 =$

Table 2
Measurement properties.

Measurement items	Loadings	*t*-Values	α	CR	AVE
Customer Experience Quality					
CEQ1	0.93	33.86			
CEQ2	0.89	21.81	0.91	0.94	0.80
CEQ3	0.92	28.49			
CEQ4	0.83	24.56			
CEQ5	0.84	23.40			
CEQ6	0.84	24.50			
Relationship Equity					
RE1	0.71	17.91			
RE2	0.96	22.32	0.89	0.93	0.76
RE3	0.92	20.48			
RE4	0.89	19.16			
Brand Equity					
BE1	0.79	17.39			
BE2	0.94	37.01	0.71	0.80	0.61
BE3	0.71	16.28			
Value Equity					
VE1	0.94	32.76			
VE2	0.97	35.27	0.75	0.84	0.72
VE3	0.76	13.90			
Trust in Service Providers					
TSP1	0.74	21.18			
TSP2	0.75	26.69	0.88	0.91	0.72
TSP3	0.98	44.24			
TSP4	0.98	45.47			
Trust in Social Robots					
TSR1	0.88	18.63	0.82	0.92	0.85
TSR2	0.96	21.39			

Notes: α: Cronbach's alpha; CR: composite reliability; AVE: average variance extracted.

Table 3
Discriminant validity.

	1	2	3	4	5	6
Customer Experience Quality **(1)**	(0.89)					
Relationship Equity **(2)**	0.51	(0.87)				
Value Equity **(3)**	0.50	0.510	(0.85)			
Brand Equity **(4)**	0.38	0.44	0.55	(0.78)		
Trust in Service Providers **(5)**	0.41	0.52	0.39	0.44	(0.85)	
Trust in Social Robots **(6)**	0.36	0.49	0.57	0.45	0.51	(0.92)

Note: Diagonal values are square roots of the AVE values.

0.69) and trust in social robots ($R^2 = 0.71$), are also acceptable.

Next, we performed blindfolding analysis with an omission distance of 7 to support the predictive relevance of the structural model (Tenenhaus et al., 2005). Results show that the redundancy (Q^2) values of experience quality, trust in service providers, and trust in social robots are >0.4, which supports the predictive validity of the proposed structural model in this study (Hair et al., 2017). We also used the PLSpredict algorithm to provide further support for the predictive relevance of our research model (Shmueli et al., 2019). Since the $Q^2_{predict}$ values of the constructs were higher than zero, it shows that the proposed research performs better than the most naïve benchmark model.

Results (shown in Table 4) of the PLS path analysis show that value equity ($\beta = 0.03$, $p < 0.28$, $t = 0.59$) has no significant effect on trust in social robots, indicating no support for hypothesis H1a. However, brand equity ($\beta = 0.28$, $p < 0.01$, $t = 3.38$) and relationship equity ($\beta = 0.29$, $p < 0.05$, $t = 4.32$) have positive and significant impacts on trust in social robots supporting H2a and H3a. We also find that value equity ($\beta = 0.19$, $p < 0.01$, $t = 3.49$), brand equity ($\beta = 0.42$, $p < 0.05$, $t = 6.85$) and relationship equity ($\beta = 0.31$, $p < 0.05$, $t = 4.52$) have significant influence on trust in service providers supporting hypotheses H1b, H2b, and H3b. Results support H4 and H6 as trust in service providers has positive and significant impact on trust in social robots ($\beta = 0.41$, $p < 0.05$, $t = 6.22$) and customer experience quality with social robots ($\beta = 0.34$, $p < 0.05$, $t = 4.74$). Finally, we found support for H5 as trust in social robots positively and significantly influences the relationship

Table 4
Results of path analysis.

Hypothesized paths	Path coefficient	*t*-Value	*p*-Value	Result	
Direct effects					
(H1a) Value Equity ➔ Trust in Social Robots	0.03	0.59	0.28^{ns}	Not Supported	
(H1b) Value Equity ➔ Trust in Service Provider	0.19	3.49	0.00**	Supported	
(H2a) Brand Equity ➔ Trust in Social Robots	0.28	3.38	0.001*	Supported	
(H2b) Brand Equity ➔ Trust in Service Provider	0.42	6.85	0.00**	Supported	
(H3a) Relationship Equity ➔ Trust in Social Robots	0.29	4.32	0.00**	Supported	
(H3b) Relationship Equity ➔ Trust in Service Provider	0.31	4.52	0.00**	Supported	
(H4) Trust in Service Provider ➔ Trust in Social Robots	0.41	6.22	0.00**	Supported	
(H5) Trust in Social Robots ➔ Customer Experience Quality	0.34	4.74	0.00**	Supported	
(H6) Trust in Service Provider ➔ Customer Experience Quality	0.34	4.60	0.00**	Supported	
Indirect effects					
				LCI	UCI
(H7a) Value Equity ➔ Trust in Service Provider ➔ Customer Experience Quality	0.07	2.99	0.00*	0.03	0.12
(H7b) Brand Equity ➔ Trust in Service Provider ➔ Customer Experience Quality	0.15	4.01	0.00*	0.08	0.23
(H7c) Relationship Equity ➔ Trust in Service Provider ➔Customer Experience Quality	0.11	2.96	0.00*	0.06	0.18
(H8a) Value Equity ➔ Trust in Social Robots ➔ Customer Experience Quality	0.01	0.62	0.53^{ns}	−0.02	0.05
(H8b) Brand Equity ➔ Trust in Social Robots ➔ Customer Experience Quality	0.07	2.74	0.00**	0.02	0.13
(H8c) Relationship Equity ➔ Trust in Social Robots ➔ Customer Experience Quality	0.10	2.78	0.00*	0.04	0.17

Note: LCI: Lower confidence interval; UCI: Upper confidence interval.
* Indicates $p < 0.05$.
** Indicates $p < 0.01$.
^{ns} Indicates not significant.

equity with social robots ($\beta = 0.34$, $p < 0.05$, $t = 4.60$).

Next, we tested the mediation hypotheses using bias-corrected, bootstrapped confidence intervals of indirect effects (Nitzl et al., 2016; Preacher and Hayes, 2008). The reported indirect effects (through trust in service provider) between value equity ($\beta_{indirect} = 0.07$, $p < 0.05$; LCI $= 0.03$, UCI $= 0.12$), brand equity ($\beta_{indirect} = 0.15$, $p < 0.05$; LCI $= 0.08$, UCI $= 0.23$) and relationship equity ($\beta_{indirect} = 0.11$, $p < 0.05$; LCI $= 0.06$, UCI $= 0.18$) and customer experience quality are significant as the respective confidence intervals do not include zero. Hence, hypotheses H7a, H7b, and H7c are supported, and we can conclude that trust in service providers mediates the relationship between customer equity drivers and customer experience quality (Fig. 3).

The reported indirect effect (through trust in social robots) between value equity and customer experience quality ($\beta_{indirect} = 0.01$, $p > 0.5$; LCI $= -0.02$, UCI $= 0.05$) is not significant as the confidence intervals include zero. Hence, H8a is not supported. The indirect effects (through trust in social robots) between brand equity ($\beta_{indirect} = 0.07$, $p < 0.05$; LCI $= 0.02$, UCI $= 0.13$) and relationship equity ($\beta_{indirect} = 0.10$, $p < 0.05$; LCI $= 0.04$, UCI $= 0.17$) and customer experience quality are significant, and the confidence intervals exclude zero. This shows that trust in social robots mediates the relationship between brand equity and customer experience quality and the relationship between relationship equity and customer experience quality. Thus, hypotheses H8b and H8c are supported.

6.3. *Artificial neural network (ANN) analysis*

6.3.1. *Validations of neural networks*

The PLS-SEM analysis confirmed all the hypothesized relationships except the relationship from value equity to trust in social robots. Accordingly, all the hypothesized relationships supported in the PLS-SEM analysis are used to create three ANN models (see Appendix B) (Chong, 2013; Xiong et al., 2022). Specifically, all three customer equity drivers are used as inputs to predict trust in service providers (ANN Model A). Next, brand equity, relationship equity and trust in service providers are used to predict trust in social robots (ANN Model B). Finally, trust in service providers and trust in social robots are used as inputs to predict customer experience quality (ANN Model C). The predictive accuracy of the models was evaluated through the metric of Root Mean Square of Error (RMSE) where small values of RMSE indicate high prediction accuracy (Wang et al., 2022). As illustrated in Table 5, all the RMSE values for the three ANN models for this study have very small values and are <0.5, indicating high prediction accuracy (El-Masri et al., 2022). In addition, R-square values are calculated to determine the percentage of variance explained by each neural network model (Xiong et al., 2022). As shown in Table 5, the input neurons explain 62.90 %, 66.44 % and 81.76 % of the variance in trust in service providers (ANN Model A), trust in social robots (ANN Model B) and customer experience quality (ANN Model C), respectively.

6.3.2. *Ranking of factors*

Normalized importance scores (sensitivity analysis) are calculated to assess the contribution of each of the input neurons on the output variable for the three ANN models. The normalized importance score is a ratio calculated by dividing the relative importance of each input neuron by the input variable having the largest relative importance (Khan et al., 2022; Wang et al., 2022). The results are reported in Table 6. It shows that brand equity is the most influential predictor for trust in service providers, followed by relationship equity and value equity (ANN Model A). In addition, trust in service providers is the most critical factor for trust in social robots, followed by relationship and brand equity (ANN Model B). Finally, trust in service providers is the most important driver for customer experience quality, followed by trust in social robots (ANN Model C). Finally, the normalized importance results from the ANN analysis were compared with the path coefficient results obtained from PLS-SEM for all the models and are presented in Table 7. It shows that the results obtained from using the two-step hybrid PLS-SEM-ANN approach are consistent, as the relative importance of the significant constructs are the same (Ng et al., 2022; Talukder et al., 2020).

7. Discussion and implications

Our study offers several theoretical contributions. First, results suggest that the three key customer equity drivers (i.e., value equity, brand equity, and relationship equity) influence trust in service providers (Ramaseshan et al., 2013). However, only brand and relationship equity impact trust in social robots. The non-significant relationship between value equity and trust in social robots may stem from the fact that

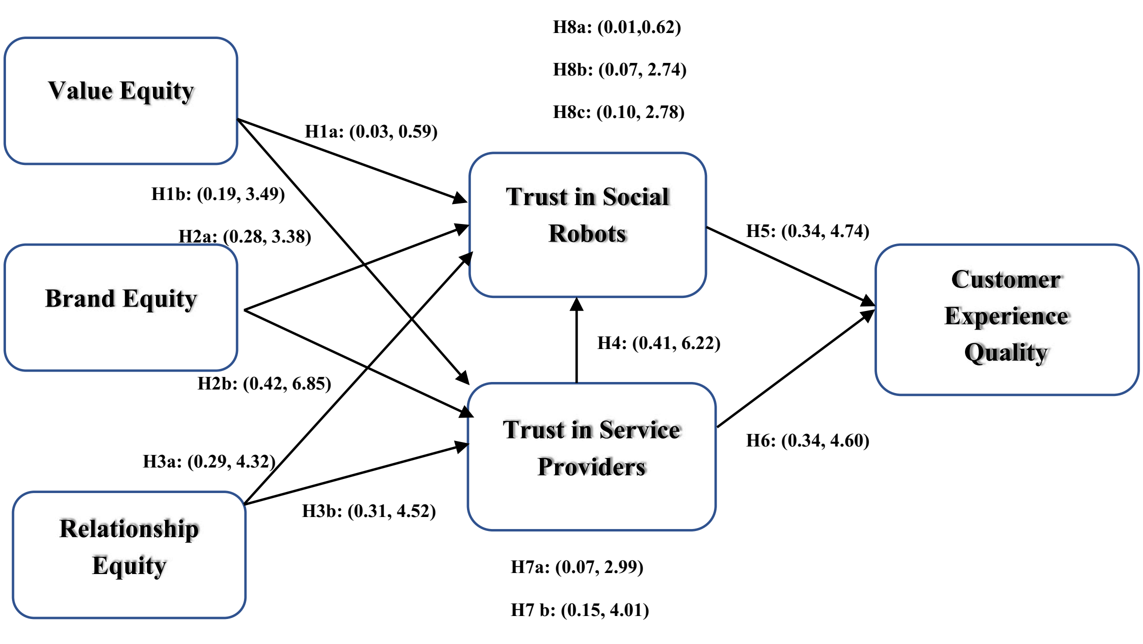


Fig. 3. Structural model results.

Table 5
Root-mean-square error (RMSE) values obtained during the training and testing stages.

Neural network	ANN Model A (R^2 = 62.90 %)						ANN Model B (R^2 = 66.44 %)						ANN Model C (R^2 = 81.76 %)					
	Training			Testing			Training			Testing			Training			Testing		
	N	RMSE	SSE	N	RMSE	SSE	N	RMSE	SSE	N	RMSE	SSE	N	RMSE	SSE	N	RMSE	SSE
ANN 1	337	0.070	1.643	40	0.060	0.145	337	0.081	2.202	40	0.089	0.318	336	0.134	6.023	41	0.121	0.599
ANN 2	339	0.071	1.700	38	0.066	0.168	339	0.082	2.305	38	0.074	0.210	334	0.134	6.031	43	0.127	0.69
ANN 3	338	0.072	1.771	39	0.072	0.202	338	0.080	2.190	39	0.079	0.245	336	0.133	5.907	41	0.130	0.696
ANN 4	333	0.074	1.827	44	0.070	0.217	333	0.083	2.285	44	0.059	0.154	330	0.134	5.949	47	0.145	0.992
ANN 5	328	0.081	2.162	49	0.073	0.258	328	0.083	2.255	49	0.057	0.159	345	0.134	6.208	32	0.145	0.673
ANN 6	342	0.081	2.233	35	0.079	0.218	342	0.080	2.207	35	0.080	0.222	338	0.133	5.989	39	0.154	0.921
ANN 7	335	0.074	1.835	42	0.060	0.149	335	0.082	2.262	42	0.064	0.171	332	0.140	6.527	45	0.107	0.516
ANN 8	340	0.069	1.613	37	0.048	0.087	340	0.083	2.342	37	0.089	0.293	345	0.136	6.395	32	0.096	0.295
ANN 9	332	0.068	1.549	45	0.051	0.118	332	0.079	2.097	45	0.071	0.227	329	0.135	5.996	48	0.120	0.69
ANN 10	340	0.078	2.068	37	0.073	0.197	340	0.080	2.168	37	0.071	0.185	336	0.128	5.542	41	0.164	1.101
Average		0.074	1.840		0.065	0.176		0.081	2.231		0.073	0.218		0.134	6.057		0.131	0.717
Standard Deviation		0.004	0.226		0.010	0.049		0.001	0.069		0.011	0.052		0.003	0.258		0.020	0.224

Notes:
1. Model A: Input neurons are value equity, brand equity, and relationship equity, while output neuron is trust in service provider.
2. Model B: Input neurons are brand equity, relationship equity, and trust in service provider, while output neuron is trust in social robots.
3. Model C: Input neurons are trust in service provider and trust in social robots, while output neuron is customer experience quality.
4. $R^2 = 1 - RMSE/S^2$, where S^2 is the variance of the desired output for the test data.

Table 6
Sensitivity analysis.

Neural network	ANN Model A			ANN Model B			ANN Model C	
	Output: Trust in Service Provider			Output: Trust in Social Robots			Output: Customer Experience Quality	
	Value Equity	Brand Equity	Relationship Equity	Brand Equity	Relationship Equity	Trust in Service Providers	Trust in Service Providers	Trust in Social Robots
Iteration 1	0.290	0.388	0.322	0.129	0.275	0.596	0.505	0.495
Iteration 2	0.361	0.356	0.282	0.235	0.267	0.498	0.590	0.410
Iteration 3	0.166	0.425	0.409	0.209	0.234	0.556	0.539	0.461
Iteration 4	0.315	0.362	0.323	0.176	0.308	0.516	0.525	0.475
Iteration 5	0.297	0.319	0.384	0.208	0.259	0.533	0.531	0.469
Iteration 6	0.158	0.450	0.392	0.238	0.248	0.514	0.486	0.514
Iteration 7	0.351	0.247	0.402	0.176	0.302	0.522	0.613	0.387
Iteration 8	0.369	0.312	0.319	0.176	0.234	0.590	0.544	0.456
Iteration 9	0.278	0.421	0.301	0.210	0.280	0.510	0.553	0.447
Iteration 10	0.163	0.350	0.487	0.271	0.257	0.472	0.540	0.460
Average relative importance	0.275	0.363	0.362	0.203	0.266	0.531	0.543	0.457
Normalized relative importance (%)	75.702 %	100.000 %	99.752 %	38.214 %	50.198 %	100.000 %	100.000 %	84.298 %

sacrifices associated with social robots are perceived as exceeding their benefits (Leroi-Werelds, 2019). Replacing people with social robots potentially reduces relational benefits; after all, robots may lack the authenticity and friendliness of a human employee. However, this negative aspect may not necessarily be detrimental to the service provider (or customer) if social robots can perform the required tasks with greater efficiency, meeting customers' need for convenience (e.g., error-free, and quick checkouts) instead (Dekimpe et al., 2020). We suspect that whether customers seek more utilitarian or social benefits from interactions with service providers depends on boundary conditions, including industry and type of service provided. For example, in the context of retail banking, utilitarian aspects (i.e., the successful completion of a transaction) often matter more than having, say, a friendly chat (Amelia et al., 2022). Further, the literature has emphasized the role of customer equity drivers in fostering satisfaction (Hao and Chon, 2022) and loyalty intentions (Vogel et al., 2008). Our findings add to this body of knowledge by highlighting the importance of customer equity drivers in developing trust, both in service providers and social robots (Hao and Chon, 2022; Cuong et al., 2020). This finding supports Hao and Chon's (2021) and other scholars' (e.g., Ramaseshan et al., 2013; Rust et al., 2001) findings that customer equity significantly enhances trust with service providers and social robots.

Second, results also reveal that trust in service providers mediates the relationship between value equity, brand equity, relationship equity, and customer experience quality. Further, trust in social robots only mediates the relationship between two equity drivers (brand equity and relationship equity) and customer experience quality and not the value equity-experience quality relationship. These findings extend the literature that advocates for a direct relationship (and not a mediating one) between customer equity drivers and customer experience quality (Gao et al., 2020). Also, this mediation of trust in service providers and trust in social robots in explaining the relationship between customer equity drivers and customer experience quality is consistent with the critical premise of relationship commitment theory, which proposes that trust in exchange partners is a crucial mediating variable between service and relational outcomes (Morgan and Hunt, 1994). The mediating relationship (vs. direct relationship) between customer equity drivers and customer experience quality is a welcome addition to the technology-mediated interactions that produce high uncertainty, for example, when interacting with social robots. Overall, this result confirms the findings of Ramaseshan et al. (2013), who have—albeit in a business-to-business context—highlighted the mediating role of trust between customer equity drivers and customer experience quality.

Third, the study findings prove that trust in service providers is

Table 7
Comparison of PLS-SEM and ANN results.

Path relationship	PLS path coefficient	ANN normalized relative importance (%)	Ranking based on PLS path coefficient	Ranking based on ANN normalized relative importance (%)	Comment
ANN Model A					
Value Equity ➔ Trust in Service Providers	0.19	75.702 %	3	3	Matched
Brand Equity ➔ Trust in Service Providers	0.42	100.000 %	1	1	Matched
Relationship Equity ➔ Trust in Service Provider	0.31	99.752 %	2	2	Matched
ANN Model B					
Brand Equity ➔ Trust in Social Robots	0.28	38.214 %	3	3	Matched
Relationship Equity ➔ Trust in Social Robots	0.29	50.198 %	2	2	Matched
Trust in Service Providers ➔ Trust in Social Robots	0.41	100.000 %	1	1	Matched
ANN Model C					
Trust in Service Providers ➔ Customer Experience Quality	0.34	100.000 %	1	1	Matched
Trust in Social Robots ➔ Customer Experience Quality	0.34	84.298 %	2	2	Matched

crucial in shaping trust towards social robots. This is consistent with the notion of initial trust being influential, as proposed by McKnight et al. (1998), which refers to trust in an unfamiliar party. Customers without prior interaction with technology (including social robots) cannot develop trust based on direct experience. In such instances, customers rely on other information about the service provider to form assumptions about how much they can trust social robots. Thus, initial trust is established through other cues, which implies that, even in the absence of social robots, customers can still place varying levels of trust in them, depending on their experiences with and opinions about the service provider.

Additionally, our study offers valuable insights for service providers adopting social robots in their operations. To optimize customer experiences with social robots, businesses should focus on enhancing relationship equity and brand equity, implying that for service providers, emphasizing brand and relationship equity is vital, as these factors directly impact customers' trust in the provider. When trust in service providers is present, customers' trust in social robots will be easier to obtain. Building a strong brand identity and nurturing long-term customer relationships can lead to greater trust, positively influencing customers' perceptions of social robots. Thus, retailers should prioritize trust-building initiatives as trust in service providers significantly mediates between customer equity drivers and customer experience quality. Transparent and reliable services, consistent communication, and delivering on promises can reinforce trust and positively impact customer experiences with social robots.

As relationship equity is a critical contributor that can drive trust in service providers and trust in social robots. Retailers should enhance relationship equity by establishing healthy customer relationships that will further bind them to the company. To achieve this, initiatives such as promoting brand communities, loyalty programs, and instituting a learning relationship with customers can be adopted as critical strategies (Lemon et al., 2001). This is consistent with the recommendation proposed by Barnes (2001) that it's all about how customers feel. In addition, retailers can focus on value equity by delivering value to customers through different aspects, including service quality, price, and an immersive shopping environment, thereby enhancing trust in the retailers (i.e., service providers).

Understanding the mediation role of trust in social robots, service providers should also aim to optimize trust levels in this technology. Effective communication about the benefits and functionalities of social robots, personalized interactions, and addressing customers' concerns can enhance trust and improve their experience with social robots. To leverage trust synergy, different stakeholder groups (including but not limited to retailers) should create a seamless integration between human service providers and social robots. The result could be a cohesive and trustworthy service environment that instils confidence in customers' interactions with both human and robotic service providers. Regularly assessing customer feedback and preferences related to social robots can help refine strategies and enhance overall customer experiences.

Additionally, educating customers about social robots' reliability, security, and benefits is essential. Clear communication can dispel uncertainties and enhance customers' trust in this emerging technology. For example, service providers can create a positive customer experience with social robots, foster trust, and strengthen customer relationships through these changes. This approach can lead to increased customer satisfaction, loyalty to the retail store, and a competitive advantage in the growing social robotics market in the retailing sector.

Our results reveal that brand equity is the most essential variable contributing to developing trust in service providers, followed by relationship and value equity. Therefore, managers should prioritize establishing and sustaining brand equity to influence trust in service providers. There are several building blocks to developing brand equity, such as building brand awareness, improving brand image, and maintaining a brand's promise to surpass customers' expectations. This is consistent with the strategies adopted by several retailers such as Walmart, H&M, IKEA, and Tesco that have leveraged the powerful image of their respective brands (Grewal et al., 2004).

8. Limitations and future research directions

Despite some advancements in literature, the study still brings some limitations. First, the data were collected with respondents from a single country—Australia, which restricts the results' generalizability. Indeed, studies have shown varying results when investigating the phenomenon of social robots across different cultures (e.g., Gasteiger et al., 2021). This underscores the need for further investigation into contextual factors, including culture. For example, we should delve into questions like: How does culture, and which cultural elements, shape our trust in social robots and the overall quality of our interactions with them?

Second, our findings are limited to the context of tangible social robots delivering services. To validate and extend our work, future research should test our findings on other robots, including virtual ones. Third, this study used a dual-staged analytical PLS-SEM-ANN methodology to test the conceptual model; further research should apply multi-staged analytical methods with a more robust predictive capability. Finally, future studies may assess how situational (e.g., perceived health risks) and psychological factors (e.g., stress) linked with extenuating situations like a pandemic can affect consumers' perceived value towards social robots and their impact on their experience.

CRediT authorship contribution statement

Sanjit K. Roy: Conceptualization, Methodology, Data Curation, Data Analysis, Supervision, Writing, Project Administration.

Gaganpreet Singh: Writing, Review & Editing, Resources, Data Visualization.

Saalem Sadeque: Data Curation, Data Analysis, Data Visualization, Writing, Editing.

Richard Gruner: Writing, Review & Editing.

Data availability

The data that has been used is confidential.

Appendix A. (Adapted from Kim et al., 2022)

Description of social robots

Before we ask you to answer the survey questions, we would like to give you some information about service robots. Please read the description below carefully:

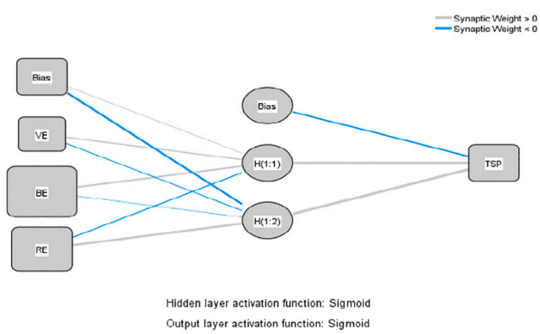
Social robots are designed to independently deliver customer service. Social robots are system-based autonomous and adaptable interfaces that interact and communicate with customers in a human-like way through speech interactions complemented with gestures and facial expressions. Social robots can recognize social circumstances and react according to human social norms. Social robots are increasingly adopted in a retail context. For example, a service robot could assist customers in locating products in a grocery store, or act as a cashier. An example of what a social robot in a retail context could look like is provided below:

Video URL

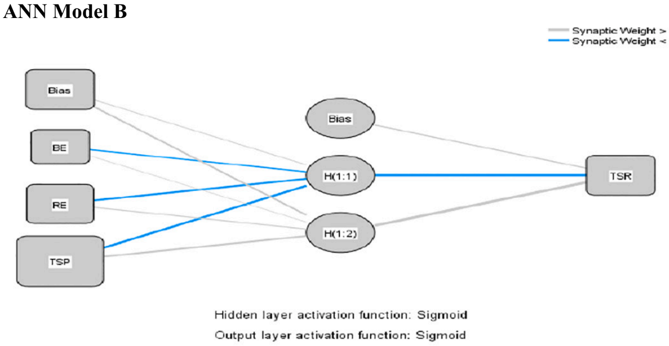
https://www.youtube.com/watch?v=y9auj2rBBYs

Appendix B

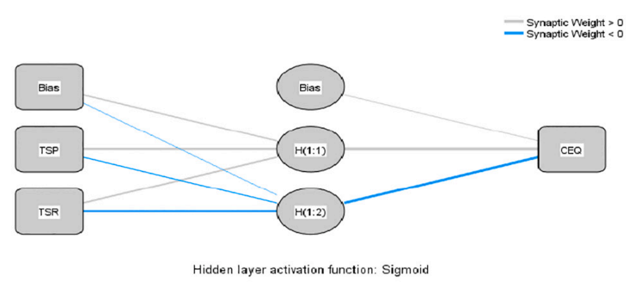
ANN Model A



ANN Model B



ANN Model C



Notes: VE = Value equity, BE = Brand equity, RE = Relationship equity, TSP = Trust in Service Provider, TSR = Trust in Social Robots, CEQ = Customer Experience Quality

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