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Relationship Quality in Customer-service Robot Interactions in Industry 5.0: An Analysis of Value Recipes

Sanjit K. Roy[1] · Gaganpreet Singh[2] · Richard L. Gruner[3,4] · Bidit L. Dey[5] · Saadia Shabnam[4] · Syed Sardar Muhammad[5] · Mohammed Quaddus[6]

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Abstract

The paper studies the interactions between customers and robots within the framework of Industry 5.0-driven services. Prior studies have explored several factors contributing to the quality of these interactions, with perceived value being a crucial aspect. This study uses *value recipes*, which refer to specific configurations of how different benefits and costs are weighed up/evaluated, as a theoretical framework to investigate the quality of relationships between customers and service robots. The study aims to shed light on the complex interplay between different value dimensions that shape customers' relationships with robots. To achieve this goal, the authors analyze what value configurations facilitate or impede high-quality relationships between customers and service robots. Fuzzy set qualitative comparative analysis (fsQCA) was used to analyze data from 326 consumers. The data reveal that *value recipes* comprising positive values (such as relational benefit, novelty, control, personalization, excellence, and convenience) and negative values (about privacy and effort) prove highly effective in augmenting relationship quality. Results also underscore those negative values either in isolation or in conjunction with positive values, do not impede relationship quality. The theoretical contribution of this study lies in presenting new insights into relationship dynamics between customers and service robots in an Industry 5.0 value-driven context. From a practical standpoint, the findings suggest guidelines for successfully infusing the retail landscape with more intelligent service robots.

Keywords Retailing · Service robots · Relationship quality · fsQCA · Value recipes · Artificial intelligence

✉ Bidit L. Dey
bidit.dey@brunel.ac.uk

Sanjit K. Roy
sanjit.roy@ecu.edu.au

Gaganpreet Singh
gaganpreet@jgu.edu.in

Richard L. Gruner
richard.gruner@uwa.edu.au

Saadia Shabnam
saadia.shabnam@curtin.edu.au

Syed Sardar Muhammad
Syed.Muhammad@brunel.ac.uk

Mohammed Quaddus
M.Quaddus@curtin.edu.au

[1] School of Business and Law, Edith Cowan University, Perth, Australia

[2] OP Jindal Global University, Sonipat, India

[3] Department of Marketing, UWA Business School, The University of Western Australia, Perth, Australia

[4] Brunel University, London, United Kingdom

[5] Curtin University, Perth, Australia

[6] School of Management and Marketing, Faculty of Business and Law, Curtin Business School, Curtin University, Perth, Australia

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1 Introduction

Industry 5.0 represents a value-centric endeavour aimed at catalyzing technological advancements with a specific purpose in mind (Xu et al., 2021). In the context of Industry 5.0, marked by the adoption of AI-based technologies, including robots, the use of service robots is evident across sectors, including tourism (Koo et al., 2018), education (Li et al., 2016), manufacturing, healthcare (Sindhwani et al., 2022), entertainment, and retail (Amelia et al., 2022). Many enterprises have embraced robots to enhance customer service across diverse industries (Grewal et al., 2020, 2021; Xiao & Kumar, 2021). For example, in the retail sector, Lowes introduced the "LoweBot" to address customer inquiries and help them locate products (Forbes Insights, 2018). Forecasts indicate that the global service robots market is poised to surge from USD 41.5 billion in 2023 to USD 84.8 billion by 2028, reflecting a robust compound annual growth rate (CAGR) of 15.4% between 2023 and 2028 (Markets & Markets, 2023).

While many studies within the field of human–robot interactions (HRI) emphasize the significance of individuals' perceptions and encounters with robots (Prati et al., 2021; Tung & Law, 2017), the exploration of the human–robot relationship's quality as a driving force within the Industry 5.0 framework remains limited (Dorai et al., 2021; Lindblom et al., 2020; Sindhwani et al., 2022). Industry 1.0 moved from manual methods to machines, Industry 2.0, with the power of electricity, to productivity and production lines, Industry 3.0 towards automation with the help of computers and communication technologies, and Industry 4.0 to make intelligent decisions in real-time with the help of technology (Xu et al., 2021). The move to Industry 5.0 requires the successful integration of perceived values with technology: a step away from digitalization and AI-driven technologies and towards long-term service to humanity (Breque et al., 2021). Moreover, the quality of the relationship between customers and service robots can be valuable when customers' perception of the perceived benefits exceeds related costs (Sirdeshmukh et al., 2002). This is consistent with the conceptualization of perceived value, which is defined as the net difference between customers' perceived benefits and costs (Sirdeshmukh et al., 2002; Zeithaml, 1988).

Prior literature has found customer-perceived value to influence relationship quality (Sirdeshmukh et al., 2002; Zeithaml, 1988). For example, Ulaga and Eggert (2006) and Moliner et al. (2007) highlight that functional, social, emotional, and relational values can influence relationship quality. However, limited research has examined how various types of values delivered by technologies, such as service robots, influence relationship quality (Zeithaml et al., 2020). Thus, this study aims to identify the *value configurations that facilitate or impede high-quality relationships between customers and service robots.* Since individual value types have complex trade-off effects, only certain combinations of value types unveil the complex value patterns contributing to such value integration in the context of Industry 5.0. With this in mind, the present study is not limited to identifying specific values in isolation that are likely to influence relationship quality. Rather, the study empirically validates *value recipes*, which refer to the multiple, distinct, combinations of positive and negative values (Leroi-Werelds, 2019) that, in turn, can affect the quality of relationships between customers and service robots.

To achieve this research aim, this study applied Leroi-Werelds' (2019) value typology, which is an evolved conceptualization of value and considers both the positive and negative aspects of value. Positive values represent benefits and negative values represent costs. It considers the infusion of technological advancements into businesses and the use of service robots. This value typology compliments Novak and Hoffman's (2019) approach of theorizing the customer-service robot relationship to be object-centered [e.g., service robots] because service robots exhibit varying degrees of agency, autonomy, and authority and it is essential to consider these terms (Canniford & Bajde, 2016). In addition to value typology, this study grounds the propositions in social exchange theory to define and characterize the reciprocal interaction between customers and service robots (Blau, 1964).

A configurational analysis using fuzzy-set qualitative comparative analysis (fsQCA) (Ragin, 2009) is performed in this study to identify *value recipes*. fsQCA is proposed to be an appropriate technique for theory building (Fiss, 2011; Pappas & Woodside, 2021) as it can recognize the complex relations among variables and offer multiple solutions that explain an outcome. The results of this study reveal a *value recipe* consisting of positive values (relational benefit, novelty, control, personalization, excellence, and convenience) and negative values (privacy and effort) that are highly effective in enhancing relationship quality. The results also highlight negative values alone or in combination with positive values that do not impede relationship quality. Overall, the results show multiple, distinct, and equally effective combinations of customers' perceived values (positive and negative values) acting as antecedents that facilitate or impede customers' quality of relationship with service robots.

The findings carry immense practical implications. The results are likely to act as suggestive guidelines for successfully infusing more intelligent technologies, including robots, in retail. The results allow managers to better understand their customer-perceived value types that influence quality relationships with service robots.

1.1 Background: Service Robots in Retail

Service robots are "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p. 3). Wirtz et al. (2019) categorize service robots by the type of service. Specifically, they classify service robots by considering whether a service is targeted at people or possessions (person vs. object) and whether these services are tangible or intangible (tangible vs. intangible). This study fits into the context of a tangible robot having a physical and/or humanoid appearance delivering a service to people's possessions (Fig. 1). Service robots enable service providers to interact with customers efficiently and effectively and, eventually, nurture the relationships between service providers and customers (Marinova et al., 2017). Apart from the functional aspects of service robots, the perceived fun and enjoyment are likely to contribute to the relationship quality between customers and service robots.

1.2 Theoretical Background: Social Exchange Theory

Social exchange theory (SET, Blau, 1964) is the key theoretical underpinning used in this study to effectively investigate the relationship between variables. SET is built on the premise that exchanges in a relationship are driven by economic (such as perceived value) and social benefits (Wisker, 2020). According to SET, customers are anticipated to reciprocate positive thoughts, feelings, and behaviors toward an object (e.g., a service robot) upon obtaining certain benefits from the service-robot relationship (Chou et al., 2021; Hollebeek, 2011; Kim et al., 2022). For a customer in an exchange with a service robot, what they give may be perceived as a cost, while what is received may be viewed as benefits, and the individual's behavior is modified as the difference between the two changes (Homans, 1958).

Social exchange encompasses unnamed obligations, whereby one party (e.g. the service robot) doing another (e.g. the customer) a favour (e.g. by providing exceptional service), is encouraged by the aim of some future return (e.g. customer loyalty; Rousseau, 1989). Thus, consistent with the fundamental premise of SET, the relationship between customers and service robots is built on the notion of reciprocity. The traditional meaning of reciprocity means an immediate return of benefits. However, the literature also acknowledges reciprocity as "a provision of favours, or the making of allowances for the other in return for similar favours/allowances to be received at a later date" (Sin et al., 2005, pp. 187–188). Therefore, customer-service robot reciprocity may evolve from a series of accumulated perceived service robot benefits, rather than being restricted to a single (e.g. the most recent) interaction. Hence, in this study, SET is applied to investigate consumers' evaluation of their benefits against relevant costs, represented by positive and negative values that are likely to contribute to building relationship quality with service robots.

1.3 Relationship Quality

Relationship quality refers to the 'degree of appropriateness of a relationship to fulfil the needs of the customer associated with the relationship' (Hennig-Thurau & Klee, 1997, p. 751). As one of the fundamental building blocks for the development of the attitude toward the organization (Moliner et al., 2007), relationship quality is also perceived as a buyer's trust in the other party and satisfaction in the relationship (Crosby et al., 1990).

Relationship quality is not only cognitive but also affective. This implies the customer's assessment of the

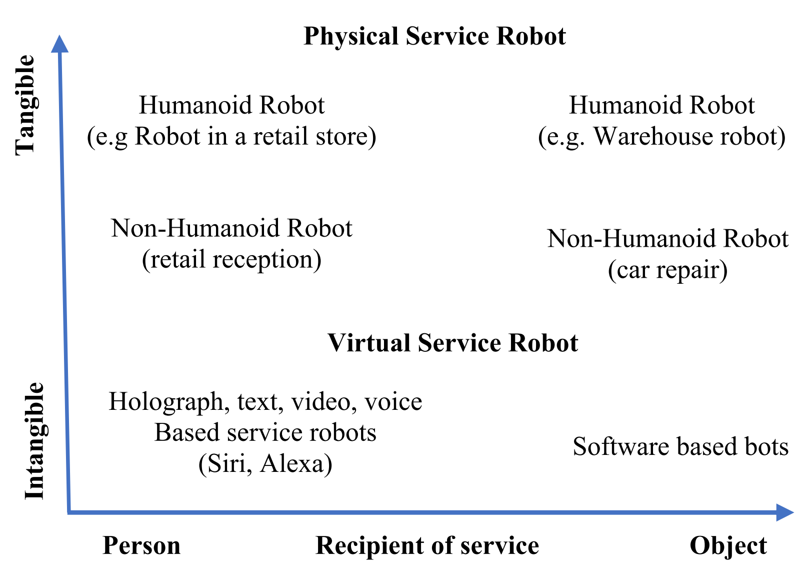

Fig. 1 Types of robots (Adapted from Wirtz et al., 2018)

relationship is not just driven by factual analysis; rather emotions and feelings also contribute significantly towards relationship quality. Moreover, relationship quality is subjective, and it varies over time. Thus, during the initial stages of a relationship customer-perceived value of each transaction is of great importance; yet, as the relationship matures, the quality of the relationship becomes a vital metric. Thus, as time progresses, customers' expectations digress from the supremacy of transactional factors to a larger focus on relational variables (Ravald & Grönroos, 1996).

This study chooses relationship quality as the ultimate dependent variable because relationship quality is a better predictor of customers' behavioral intentions (Roberts et al., 2003). Further, Gummesson's (1987) conceptualization of relationship quality could be adapted in the context of service robots thereby reflecting the quality of the interaction between customers and a service robot, and it can be interpreted in terms of accumulated value with both positive and negative components (Moliner et al., 2007). The positive component represents benefits, and the negative component consists of costs and sacrifices associated with service robots. Athanasopoulou (2009) provides a comprehensive synthesis of previous studies on relationship quality.

There is consensus in the literature that relationship quality is a higher-order construct consisting of first-order dimensions which are satisfaction with-, trust in and commitment to the service provider (Dorai et al., 2021; Du Wulf et al., 2001; Hennig-Thurau et al., 2002). Building on the existing research, this study considers satisfaction, trust, and commitment to the relationship with a service robot to be the constituents of the relationship quality (Amin et al., 2021; Park, 2020; Roy & Eshghi, 2013).

1.3.1 Customer Satisfaction with Service Robots

Service robots can incite engagement (Nass et al., 1995), intelligence perceptions (Koda & Maes, 1996), and social interactions (Cassell, 2000), thereby establishing personal, and emotional bonds with customers (Keeling et al., 2010). Despite a significant leap forward in robot commercialization, service robots are unable to replicate humanness, enabling customers to feel a discrepancy between their expectations and their actual experiences of interacting with service robots (Mori et al., 2012; Steinhoff & Palmatier, 2021). Humanness is similar to humans (appearance, motions, own will and mind, human-essential capacities, and emotions in groups (Leyens et al., 2000). In addition, Haslam (2006) suggests humanness in the context of Human–Robot Interaction is uniquely human characteristics that lead to the perception of humans as animal-like (Cognition, intelligence, secondary emotions/morality and intentionality), and human nature characteristics that represent primary emotions, sociability or warmth (Gray et al., 2007). Hence, dehumanization or denying human essential attributes in service robots could put off and displease customers towards service robots (Westerman et al., 2020; Złotowski et al., 2014). Similar trends are captured by Masahiro Mori's uncanny valley in emotional responses from affinity to disliking service robots (Grewal et al., 2020; Strait et al., 2015).

Furthermore, the inability of service robots to imitate human behaviors prompts customer frustration and disappointment due to nonoptimal informational and service outcomes (Mimoun et al., 2012). Based on Lai's (2014) definition, satisfaction in this study is defined as the degree of customers' positive feelings and reactions toward their relationship with service robots. This satisfaction can reflect accumulated perceptions (performance vs. expectations) based on past, current, and future experiences (Byrd et al., 2021). The level of satisfaction accomplished by a customer is therefore a signal of the health of the relationship (Moliner et al., 2007).

1.3.2 Customer Commitment to the Relationship with Service Robots

The commitment represents the highest level of a relational bond between customers and service providers (Dwyer et al., 1987). It develops between the parties when one party believes that its relationship with the other is so vital that it is valuable to exert the effort to uphold it indefinitely (Keiningham et al., 2015; Morgan & Hunt, 1994). Commitment reflects long-term intentions, and a desire to make short-term sacrifices to obtain long-term benefits from a relationship (Moliner et al., 2007). It is argued that the higher the level of commitment, the more favourable the customers' perceptions of service robots (Inoue et al., 2017; Koo et al., 2020). Thus, the more robust a customer's commitment is to a service robot, the higher the customer's emotional bond toward the service robot will be (Vohra & Bhardwaj, 2019). The human–robot interaction literature also builds on the premise of the affect theory of social exchange which posits that relational cohesion is expected to result in affect. Therefore, the affective commitment would improve the relational ties between customers and service robots and eventually lead to positive outcomes (Dorai et al., 2021). Hence, commitment is considered a crucial dimension of relationship quality in the context of service robots.

1.3.3 Customer Trust in Service Robots

The other key determinant of long-term relationships is consumers' trust (Morgan & Hunt, 1994). Referring to Lee and See's (2004) definition, this study defines customers' trust in service robots as the attitude that a service robot will help accomplish the goals of the consumer in a situation characterized by uncertainty and vulnerability. Despite great potential, the vital factor that may hinder the integration of service robots in business operations is consumers' lack of trust (Everett et al., 2017; van Pinxteren et al., 2019). The literature acknowledges that trust development in HRI is a function of *human-related* (e.g., competency; comfort with a robot; propensity to trust), *robot-related* (e.g., reliability of robot; anthropomorphism) and *environmental-related factors* (e.g., culture; task type) (Hancock et al., 2011). Despite these advancements, trust has not been measured to determine consumers' enhanced value (value equity) that integrates their value with service robots required for the implementation of Industry 5.0. Therefore, trust is the vital key to determining success and retaining consumers to acquire service and information through service robots (Kok & Soh, 2020) which is imperative for the execution of Industry 5.0 (Noble et al., 2022).

1.4 Customer Value

Customer-perceived value is defined as a customer's trade-off between a product's perceived benefits (e.g., product quality) and its perceived cost or sacrifice (e.g., price; Monroe, 1990, p. 46), alluding to a customer's intuitive calculation of "give-versus-get" (Zeithaml et al., 2020). The literature acknowledges several value typologies. This study adapted Leroi-Werelds's (2019) updated value typology that considers the change in value perceptions that occurs due to the infusion of new-age technologies including service robots (Leroi-Werelds, 2019). Leroi-Werelds (2019) updated the typology of customer-perceived value consisting of 14 positive and 10 negative value types. Since customer-perceived value is situation-specific and given the focus on service robots in the context of Industry 5.0 in this study, as suggested by (Leroi-Werelds, 2019) only those value types that are influenced by the human/technology interface are included in the paper. The positive values (benefits) used in this study include convenience (efficiency), excellence, status, enjoyment (play), personalization, control, novelty, and relational benefits. The negative values (cost) used in this study include effort, privacy risk, security risk, and performance risk.

As the application of robotics in the retail environment is likely to generate both perceived benefits and costs for consumers, customer-perceived value, in this case, is a combination (or configuration) of these variables that is most effective in explaining its outcomes (Misangyi & Acharya, 2014; Misangyi et al., 2017). Indeed, the pertinent literature reveals that customer behavior has a complex and non-linear pattern. Multiple determinants contribute to this pattern, and it is influenced by various antecedent factors. These factors are activated in a different sequence and carry variable weightings. According to Lucas et al. (2008), understanding customer behavior requires considering these intricacies and the interplay between different factors. The relationship between robots and consumers in a retail context is complex due to factors such as novelty, emotional connection, trust, adaptation, and ethical considerations across digital, physical, and social dimensions (e.g., Bolton et al., 2018). Hence, consumers may feel overwhelmed, uncertain, and skeptical about interacting with robots in a retail context. Thus, addressing these complexities is crucial for successful integration and fostering positive consumer relationships with (retail) robots. To do so, we propose, a more nuanced view that explores relationship quality under distinct combinations of contextual factors.

Against this backdrop, we propose:

> Proposition 1: The presence of both positive values (such as convenience, excellence, and others) and negative values (such as effort, security risk, and others) is a prerequisite condition (for a value recipe) to predict the relationship quality of human-robot interactions in a retail setting.

The positive values represent benefits, and the negative values highlight costs received by the customer in the human–robot interaction.

Based on the above analyses of the positive and negative dimensions the following is proposed.

> Proposition 2: The combined presence of positive and negative service values (value recipe) can either increase or decrease the relationship quality because each value component contributes differently to the human-robot relationship quality in a retail setting.

2 Value Recipe: The Configurational Model

As the prediction of the relationship quality construes a complex social phenomenon, a set of complex interactions or 'configurations' among antecedent factors must be considered to develop a causal model capable of predicting the condition that leads to the desired outcome. For this research, configurational modelling (Olya et al., 2018; Rihoux & Ragin, 2008) has been adopted to demonstrate the complexities, encapsulating the 'recipe' of causal antecedents to explain the required conditions leading to a set of preferred outcomes. This study has selected a set of positive and negative values as the ingredients of a causal configuration which are introduced here as the *value recipe*. Thus, the *value recipe* is the desired combination of value types capable of predicting the relationship quality of human–robot interaction in a retailing setting (i.e., outcome). In the current study, consistency and coverage are two criteria for refining and selecting causal models that can explain the perfect *value recipe* for the desired relationship quality of human–robot interaction in retailing. As mentioned earlier, in the current study fsQCA (Pappas & Woodside, 2021; Ragin, 2009) is used to develop the *value recipe*. As per fsQCA consistency and coverage are two criteria for refining and selecting causal models that can explain the perfect *value recipe* for the desired relationship quality of human–robot interaction in retailing. The methodological procedure of fsQCA along with the concepts of consistency and coverage are described in the following section.

3 Methodology

3.1 Fuzzy Set Qualitative Comparative Analysis (fsQCA)

This study uses fsQCA to explore which combination of antecedent variables (positive and negative values) facilitates or inhibits 'relationship quality. Extant research in business and management recognized that management outcomes did not depend on the net effect of any single antecedent variable. A combination (or configuration) of variables is most effective for explaining the outcomes properly (Misangyi & Acharya, 2014; Misangyi et al., 2017). Besides taking the configuration approach, two other most important characteristics of fsQCA are (i) *equifinality*, i.e., there are multiple ways to reach an outcome and fsQCA finds most of them; and (ii) *asymmetry*, i.e., high values of antecedents (X) do not always produce high values of outcomes (Y). In r, low values of X may also produce high values of Y (Woodside, 2013). fsQCA can handle asymmetric relationships appropriately. Simple scatter plots of this study data have revealed asymmetric relationships between the positive/negative values and relationship quality (For example, see Appendix 2). Hence, fsQCA is the appropriate method for this study.

fsQCA requires several steps as follows (Greckhamer et al., 2018; Lewellyn & Muller-Kahle, 2021; Pappas & Woodside, 2021; Schneider & Wagemann, 2010): (i) transform data into fuzzy sets by choosing various thresholds (full fuzzy membership, full fuzzy non-membership, and crossover point), (ii) perform necessary analysis, (iii) develop truth table, and (iv) conduct sufficiency analysis based on truth table solutions (configurations). In addition to the above, this study also performed contrarian case analysis and predictive validity tests as suggested by Pappas and Woodside (2021).

Two important concepts are used in fsQCA to evaluate a configuration: consistency and coverage. Consistency (0 to 1) refers to the degree to which a configuration leads to the outcome in question (Lewellyn & Muller-Kahle, 2021; Ragin, 2008). This is equivalent to significance in a statistical sense. The recommended threshold value for consistency in fsQCA is 0.8 (Rihoux and Ragin, 2009). Coverage (0 to 1), on the other hand, assesses the degree to which a cause or causal combination accounts for instances of an outcome (Ragin, 2008). Thus, coverage gauges the empirical relevance or importance of a configuration. The recommended minimum value for coverage is 0.50 (Ragin, 2008).

3.2 Sampling

To explore the propositions, a questionnaire was developed. The study utilized a realistic written scenario to help consumers visualize the use of service robots (Appendix 1). Scenarios offer alternative examples of the world. They enable the ability to anticipate behavior by exploring the limitations or transformations in an external environment, or the association between forces (Curry et al., 2006). A good scenario is feasible, in terms of it resembling future trends, and that can be 'imagined' by the viewer (Curry et al., 2006). The scenario described basic information about the service robot and how it functions in retail.

To limit confounding effects and ensure scenario actuality, the scenario was tested as follows (Tombs & McColl-Kennedy, 2013). First, the scenario was adapted from the relevant literature to ensure it meets the criterion to qualify for the service robot context (Kim et al., 2022). Second, the scenario was run through a services marketing professors from a leading business school in Australia and the United Kingdom. The complete text scenario and related video are shown in Appendix 1. The actuality of the scenario was empirically tested using the following three-item scale (Henkens et al., 2021): (1) What is described in this scenario could also happen in real life, (2) the scenario seems realistic, and (3) I had no difficulty imagining myself in the situation.

Considering the minimum sample size criterion for multivariate analysis (10 times more than the number of relationships in the proposed model) proposed by Hair et al., (2013), and considering the number of conditions in a configurational model for a QCA (Sukhov et al., 2023) (i.e., at least 20 observations are required, when examining the four different conditions), a sample of 326 participants was deemed appropriate for this research. A web-based survey was administered using Amazon Mechanical Turk (MTurk). All the MTurk-focused recommendations such as adequate remuneration, and approval rate were followed (Crump et al., 2013; Goodman & Paolacci, 2017). In addition, based on Pyo and Maxfield's (2021) suggestion, this study used several attention check questions (i.e., '*What is the above scenario about?*' irrespective of their answer they could proceed, but the answer was compulsory) to make sure that the respondents have paid sufficient attention to the survey.

3.3 Measures

The scales are adapted for all the constructs from existing literature. First, *convenience* was adapted from Pihlström and Brush (2008), while *excellence* was measured by adapting Gallarza et al., (2017) scale. *Status* was gauged by deploying Nasution and Mavondo's (2008) instrument, while *enjoyment* was adapted from Gallarza et al., (2017). *Personalization* was adapted from Veloutsou and McAlonan, (2012) scale. *Control* was measured by adapting items proposed by Kleijnen et al., (2007), *Novelty* was adapted from Wells et al., (2010) and *Relational benefits* were measured through items proposed by Chan et al., (2010). Moreover, perceived costs (*effort, security risk, and physical risk*), were adapted from Mani and Chouk (2018). Privacy risk was measured through items adapted from Lin et al., (2005). An overview of the measurement items is shown in Table 1.

4 Data Analysis

4.1 Measurement Properties

Before running the fsQCA procedure, the factor structure and psychometric properties of the constructs were verified. All the factor loadings for each item exceeded 0.6 and were statistically significant. All the AVE scores were greater than the 0.5 thresholds, ranging from 0.569 to 0.743. Therefore, the latent variable describes more than half of its indicator variable (Hair et al., 2011). Furthermore, all constructs had Cronbach's alpha scores that were greater than the recommended 0.7 threshold, with scores ranging from 0.817 to 0.927. This demonstrates that all the items have adequate internal consistency to represent the construct. To measure the discriminant validity of the measurement model, the square root of each construct's AVE variable must be greater than the correlation between the other constructs in the model (Fornell & Larcker, 1981). In addition, the HTMT (Heterotrait-Monotrait) ratio was used to provide additional support to discriminant validity. The bootstrapping results were used and found that the HTMT values of all the constructs were less than the cut-off value of 0.85 and $p < 0.05$ (Hair et al., 2021). The discriminant validity for the model has been met for all constructs (Table 2).

4.2 Results of fsQCA

This study analyzed the data using three fsQCA models as follows.

$$rq = f(pv) \tag{1}$$

Table 1 Adapted Leroi-Werelds' (2019) value typology in robots' context

Benefits	***Convenience (efficiency)***	The extent to service robots makes the customer's life easier
	Excellence	The customer's assessment of the service robot (e.g., its overall usefulness)
	Status	The extent to which service robot customers leave a positive impression on others,
	Self-esteem	The degree to which service robots affect customer attitudes, perceptions, or satisfaction with themselves
	Enjoyment (play)	Service robot's capacity to yield customer-perceived fun, entertainment, or pleasure
	Aesthetics	The extent to service robot is perceived to be appealing or attractive (e.g., in terms of its design)
	Escapism (spirituality)	A service robot's capacity to help customers relax, unwind, or escape reality is known as its spirituality
	Personalization	The extent to which the Service robot's capacity is adaptable to individual customers' needs, wants, and desires
	Control	The extent to which customers can exert influence on their purchase/consumption process and its outcomes
	Novelty	The perceived extent to which Service robots incite customer curiosity and/or satisfy their appetite for new retail features
	Relational benefits	An important gateway to attracting other or like-minded customers to the store by permitting customers to share their Service robot's benefits with others
	Social benefits	The extent to which service robot results in better relationships with other customers
	Ecological benefits (ethics)	The extent to which service robot has a positive impact on environmental well-being
	Societal benefits	The extent to which service robot has a positive impact on social well-being
Costs	Price	The extent to which accessing service through robots is expensive
	Time	The extent to which accessing service robots requires time to prepare, use and understand
	Effort	The extent to which accessing service robots requires effort to use, understand
	Privacy risk	The extent to which accessing service robots can result in a loss of privacy
	Security risk	The degree to which accessing service robots can result in security issues
	Performance risk	The inability of the service robot to not perform as expected
	Financial risk	The extent to which service robots can result in a loss of money
	Physical risk	The extent to which service robots can result in health issues
	Ecological costs	The extent to which service robot harms environmental well-being
	Societal costs	The extent to which service robot harms social well-being

The value types (benefits/costs) stated in Bold, and *italics* are adopted in this study, as they are applicable in the context of service robots

Table 2 Discriminant validity

	1	2	3	4	5	6	7	8	9	10	11	12
Status (1)	**0.842**											
Enjoyment (2)	0.296	**0.831**										
Control (3)	0.400	0.550	**0.766**									
Convenience (4)	0.322	0.486	0.652	**0.783**								
Effort (5)	0.140	0.583	0.636	0.660	**0.829**							
Excellence (6)	0.187	0.583	0.679	0.750	0.781	**0.756**						
Novelty (7)	0.395	0.456	0.658	0.703	0.496	0.604	**0.845**					
Performance risk (8)	0.510	0.028	0.099	0.074	0.062	0.088	0.118	**0.873**				
Personalization (9)	0.276	0.547	0.698	0.603	0.672	0.748	0.609	0.003	**0.755**			
Privacy (10)	0.593	0.483	0.686	0.554	0.477	0.532	0.553	0.175	0.554	**0.846**		
Relational benefits (11)	0.583	0.448	0.669	0.689	0.531	0.581	0.703	0.282	0.556	0.733	**0.857**	
Security risk (12)	0.621	0.491	0.527	0.427	0.376	0.400	0.426	0.178	0.408	0.727	0.636	**0.862**

The bold numbers on the diagonal are square root of AVE values of the constructs

$$rq = f(nv) \tag{2}$$

$$rq = f(pv, nv) \tag{3}$$

where 'rq' is the relationship quality, 'pv' are positive values, and 'nv' are negative values. It is noted that the negation of relationship quality (ie. ~ rq) has also been executed for all the above models to find out which combinations of pv and nv will negate (impede) the relationship quality.

4.3 Data Transformation

The first step in fsQCA is to transform the data into fuzzy variables. All data has been collected using a Likert scale from 1 to 7 rating, where 1 represents strongly disagree with a statement and 7 represents strongly agree. In a fuzzy sense, a full non-membership should have a score of 0.05 and below, a full membership will have a score of 0.95 and above, and a cross-over point will have a score of 0.5 (Ordanini et al., 2014; Ragin, 2008). Based on extant literature (Ordanini et al., 2014; Pappas & Woodside, 2021), the threshold values of 6.0 (agree), 4.0 (neither agree nor disagree) and 2.0 (disagree) were used as a full membership, cross-over point, and full non-membership respectively.

4.4 Contrarian Case Analysis

Traditionally when investigating the relationship between two variables, the main positive (when x increases y increases) or negative (when x increases y decreases) relationship between the variables was tested. However, an opposite relation between the variables may exist which can be explicated through contrarian case analysis. Table 3 shows the contrarian case analysis of the data. The positive antecedents are shown on the right-hand side of the Table. Higher values of these antecedents should drive the relationship quality high (main effect shown in italics). However, Table 3 also shows that higher values of many of the antecedents drive the relationship quality low (contrarian cases shown in bold). It is noted that several contrarian cases are more prevalent for negative antecedents of relationship quality (right-hand side of Table 3). To incorporate the effects of the contrarian cases on the outcome variable (relationship quality in the case of this study) fsQCA is the ideal tool for data analysis (Pappas & Woodside, 2021). fsQCA is capable of examining the configuration of antecedent conditions (including the contrarian cases) leading to both enhancing and impeding the relationship quality.

4.5 Necessary Analysis

This study used the necessary analysis function of fsQCA 3.0 to explore the positive value necessary conditions leading to a high level of relationship quality, which is shown in Table 4. A condition is necessary (perhaps out of multiple conditions) if it is always present whenever the outcome occurs ('relationship quality' in our case) (Lewellyn & Muller-Kahle, 2021). In fsQCA a condition is necessary when its consistency value is greater than 0.9 (Pappas & Woodside, 2021; Ragin, 2008).

Table 4 reveals that all conditions are necessary (consistency > 0.9) for positive relationship quality except 'cpvenjo' (enjoyment) and 'cpvexpe' (experience) which have a consistency level of below 0.9. Hence these necessary conditions should produce the best configuration leading to a high level of relationship quality. It is observed that all conditions have good coverage (> 0.9).

Table 5 shows the necessary analysis table of negative values hindering the relationship quality. It is observed that 'cnveffo' (effort) is the only necessary condition to impede

Table 3 Results from the contrarian case analysis

Contrarian cases with positive values

Relationship quality

		1	2	3	4	5
Relational benefit (cpvrela) (Chi sq = 438.13 P = 0.00)	1	*52(13.8%)*	*11 (2.9%)*	*8 (2.1%)*	**2 (0.5%)**	**2 (0.5%**
	2	*18 (4.8%)*	*53 (14.1%)*	*13 (3.4%)*	**7 (1.9%)**	**2 (0.5%)**
	3	*3 (0.8%)*	*6 (1.6%)*	*28 ((7.4%)*	*27 (7.2%)*	*5 (1.3%)*
	4	**0 (0.0%)**	**3 (0.8%)**	*17 (4.5%)*	*33 (8.8%)*	*8 (2.1%)*
	5	**0 (0.0%)**	**1 (0.3%)**	*3 (0.8%)*	*23 (6.1%)*	*52 (13.8%)*
Novelty (cpvnove) Chi sq = 235.364 P = 0.00)	1	*39(10.3%)*	*22 (5.8%)*	*5(1.3%)*	**3 (0.8%)**	**0 (0.0%)**
	2	*17 (4.5%)*	*30 (8.0%)*	*23 (6.1%)*	**13(3.4%)**	**2 (0.5%)**
	3	*4 (1.1%)*	*6 (1.6%)*	*18 (4.8%)*	*16 (4.2%)*	*3 (0.8%)*
	4	**6 (1.6%)**	**13 (3.4%)**	*21 (5.6%)*	*45 (11.9%)*	*26 (6.9%)*
	5	**7 (1.9%)**	**3 (0.8%)**	*2 (0.5%)*	*15 (4.0%)*	*38 (10.1%)*
Control (cpvcont) Chi sq = 272.551 P = 0.00)	1	*46 (12.2%)*	*27 (7.2%)*	*10 (2.7%)*	**3 (0.8%)**	**0 (0.0%)**
	2	*12 (3.2%)*	*20 (5.3%)*	*11 (2.9%)*	**8 (2.1%)**	**1 (0.3%)**
	3	*12 (3.2%)*	*18 (4.8%)*	*28 (7.4%)*	*34 (9.0%)*	*9 (2.4%)*
	4	**2 (0.5%)**	**4 (1.1%)**	*15 (4.0%)*	*31 (8.2%)*	*10 (2.7%)*
	5	**1 (0.3%)**	**5 (1.3%)**	*5 (1.3%)*	*16 (4.2%)*	*49 (13.0%*
Personalization (cpvpers) Chi sq = 214.584 P = 0.00)	1	*38 (10.1%)*	*27 (7.2%)*	*9 (2.4%)*	**3 (0.8%)**	**2 (0.5%)**
	2	*12 (3.2%)*	*25 (6.6%)*	*18 (4.8%)*	**9 (2.4%)**	**2 (0.5%)**
	3	*8 (2.1%)*	*11 (2.9%)*	*22 (5.8%)*	*27 (7.2%)*	*7 (1.9%)*
	4	**12 (3.2%)**	**6 (1.6%)**	*14 (3.7%)*	*30 (8.0%)*	*11 (2.9%)*
	5	**3 (0.8%)**	**5 (1.3%)**	*6 (1.6%)*	*23 (6.1%)*	*47 (12.5%)*
Enjoyment (cpvenjo) Chi sq = 287.524 P = 0.00)	1	*43 (11.4%)*	*13 (3.5%)*	*8 (2.1%)*	**9 (2.4%)**	**4 (1.1%)**
	2	*23 (6.1%)*	*39(10.4%)*	*11 (2.9%)*	**7 (1.9%)**	**1 (0.3%)**
	3	*3 (0.8%)*	*16 (4.3%)*	*16 (4.3%)*	*20 (5.3%)*	*4 (1.1%)*
	4	**2 (0.5%)**	**4 (1.1%)**	*26 (6.9%)*	*39 (10.4%)*	*15 (4.0%)*
	5	**2 (0.5%)**	**2 (0.5%)**	*7 (1.9%)*	*17 (4.5%)*	*45 (12.0%)*
Experience (cpvexpe) Chi sq = 273.228 P = 0.00)	1	*39 (10.4%)*	*13 (3.5%)*	*7 (1.9%)*	**7 (1.9%)**	**2 (0.5%)**
	2	*27 (7.2%)*	*30 (8.0%)*	*12 (3.2%)*	**12 (3.2%)**	**5 (1.3%)**
	3	*5 (1.3%)*	*20 (5.3%)*	*17 (4.5%)*	*12 (3.2%)*	*4 (1.1%)*
	4	**2 (0.5%)**	**11 (2.9%)**	*31 (8.2%)*	*45 (12.0%)*	*17 (4.5%)*
	5	**0 (0.0%)**	**0 (0.0%)**	*2 (0.5%)*	*15 (4.0%)*	*41 (10.9%)*
Excellence (cpvexce) Chi sq = 228.247 P = 0.00)	1	*38 (10.1%)*	*25 (6.6%)*	*6 (1.6%)*	**2 (0.5%)**	**0 (0.0%**
	2	*13 (3.4%)*	*28 (7.4%)*	*22 (5.8%)*	**13 (3.4%)**	**1 (0.3%)**
	3	*5 (0.3%)*	*12 (3.2%)*	*18 (4.8%)*	*17 (4.5%)*	*4 (1.1%)*
	4	**12 (3.2%)**	**6 (1.6%)**	*21 (5.6%)*	*39 (10.3%)*	*24 (6.4%)*
	5	**5 (1.3%)**	**3 (0.8%)**	*2 (0.5%)*	*21 (5.6%)*	*40 (10.6%)*
Convenience (cpvconv) Chi sq = 280.846 P = 0.00)	1	*36 (9.5%)*	*21 (5.6%)*	*9 (2.4%)*	**1 (0.3%)**	**1 (0.3%)**
	2	*20 (5.3%)*	*34 (9.0%)*	*17 (4.5%)*	**11 (2.9%)**	**0 (0.0%)**
	3	*9 (2.4%)*	*15 (4.0%)*	*30 (8.0%)*	*28 (7.4%)*	*5 (1.3%)*
	4	**6 (1.6%)**	**3 (0.8%)**	*10 (2.7%)*	*31 (8.2%)*	*15 (4.0%)*
	5	**2 (0.5%)**	**1 (0.3%)**	*3 (0.8%)*	*21 (5.6%)*	*48 (12.7%)*

Contrarian cases with negative values

Relationship quality

		1	2	3	4	5
Security (cnvsecu) (Chi sq = 162.795 P = 0.00)	1	**29 (7.7%)**	**12 (3.2%)**	*2 (0.5%*	*14 (3.7%)*	*15 (4.0%)*
	2	**25 (6.6%)**	**15 4.0%)**	*11 (2.9%*	*12 (3.2%)*	*6 (1.6%)*
	3	*18 4.8%)*	*33 (8.8%)*	*15 (4.0%)*	*13 (3.4%)*	*8 (2.1)*
	4	*1 (0.3%)*	*13 (3.4%)*	*28 (7.4%)*	**20 (5.3%)**	**6 (1.6%)**
	5	*0 (0.0%)*	*1 (0.3%)*	*13 (3.4%)*	**33 8.8%)**	**34 (9.0%)**
performance risk (cnvperf) (Chi sq = 160.363 P = 0.00)	1	**17 (4.5%)**	**12 (3.2%)**	*13 (3.5%)*	*17 (4.5%)*	*19 (5.1%)*
	2	**25 (6.6%)**	**27 (7.2%)**	*5 (1.3%)*	*7 (1.9%)*	*1 (0.3%)*
	3	*17 (4.5%)*	*29 (7.7%)*	*17 (4.5%)*	*15 (4.0%)*	*3 (0.8%)*
	4	*6 (1.6%)*	*4 (1.1%)*	*23 (6.1%)*	**21 (5.6%)**	**4 (1.1%)**
	5	*8 (2.1%)*	*2 (0.5%)*	*11 (2.9%)*	**32 (8.5%)**	**41 (10.9%)**
Privacy (cnvpriv) (Chi sq = 398.636 P = 0.00)	1	**57 (15.1%)**	**19 (5.0%)**	*5 (1.3%)*	*2 (0.5%)*	*0 (0.0%)*
	2	**11 (2.9%)**	**26 (6.9%)**	*7 (1.9%)*	*5 (1.3%)*	*2 (0.5%)*
	3	*4 (1.1%)*	*20 (5.3%)*	*25 (6.6%)*	*23 (6.1%)*	*4 (1.1%)*
	4	*1 (0.3%)*	*8 (2.1%)*	*28 (7.4%)*	**44 (11.7%)**	**11 (2.9%)**
	5	*0 (0.0%)*	*1 (0.3%)*	*4 (1.1%)*	**18 (4.8%)**	**52 (13.8%)**
Effort (cnveffo) (Chi 209.283 P = 0.00)	1	**39 (10.3%)**	**38 (10.1%)**	*10 (2.7%)*	*4 (1.1%)*	*0 (0.0%)*
	2	**12 (3.2%)**	**21 (5.6%)**	*33 (8.8%)*	*19 (5.0%)*	*2 (0.5%)*
	3					
	4	*18 (4.8%)*	*13 (3.4%)*	*22 (5.8%)*	**52 (13.8%)**	**31 (8.2%)**
	5	*4 (1.1%)*	*2 (0.5%)*	*4 (1.1%)*	**17 (4.5%)**	**36 (9.5%)**

Cases in **bold** represent contrarian cases.
Cases in *italics* represent the main effect
The sets of contrarian cases are counter to the main effect size

the relationship quality. However, its coverage is very low (0.197162). Hence its empirical relevance is very low to impede relationship quality. Thus, it is not a seriously necessary condition to impede relationship quality.

4.6 Sufficiency Analysis

A condition (or configuration of conditions) is sufficient when the occurrence of this almost always leads to the occurrence of the outcome (Lewellyn & Muller-Kahle, 2021; Ragin, 2008). Thus, analysis of sufficient conditions identifies various configurations leading to the outcomes. As per Pappas and Woodside's (2021) guidelines, we have chosen threshold values for solution consistency and coverage for sufficiency analysis as greater than 0.8 and 0.5 respectively. In this study, the outcome variable is relationship quality. The antecedent conditions are positive values, negative values, and a combination of positive and negative values. The sufficiency analysis was undertaken as per the models (1), (2) and (3) presented earlier. Firstly, the truth table was developed as per the extant literature (Pappas & Woodside, 2021; Ragin, 2008). A frequency threshold of 2 was used to ensure at least 80% of the cases were analyzed (Pappas & Woodside, 2021). The consistency threshold was chosen as 0.8 to discard the low-consistent solutions (Pappas & Woodside, 2021). All these thresholds eventually produced various configurations using the truth table algorithm within fsQCA software.

Table 6 presents various configurations obtained from the truth table analysis as per the model rq = f (pv) and its

Table 4 Necessary analysis of antecedent conditions (positive values) leading to facilitate relationship quality

Conditions (positive values)	Consistency	Coverage
cpvrela	0.909559	0.970894
cpvnove	0.947503	0.913965
cpvcont	0.931143	0.934520
cpvpers	0.960019	0.909524
cpvenjo	0.867247	0.953928
cpvexpe	0.819612	0.972140
cpvexce	0.973817	0.903282
cpvconv	0.956176	0.920115

Table 5 Necessary analysis of antecedent conditions (negative values) hindering the relationship quality

Conditions (negative values)	Consistency	Coverage
cnvsecu	0.792309	0.226305
cnvperf	0.865121	0.238260
cnvpriv	0.707338	0.179293
cnveffo	0.919412	0.197162

Table 6 Configurations as per model rq = f (pv) and ~ rq = f (pv)

Configurations of positive values (pv) for predicting a high score of relationship quality	RC	UC	C	Configurations of positive values (pv) for predictinglow scores of relationship quality	RC	UC	C
Model: rq = f (pv)				Model: ~ rq = f (pv)			
Configurations:				Configurations			
(i) cpvrela*cpvnove*cpvcont*cpvpers *cpvexce*cpvconv	0.838	0.059	0.99	(i) ~ cpvrela* ~ cpvnove*cpvpers* ~ cpvenjo* ~ cpvexpe*cpvexce* ~ cpvconv	0.438	0.066	0.93
(ii) ~ cpvrela* ~ cpvnove*cpvpers* ~ cpvenjo* ~ cpvexpe*cpvexce* ~ cpvconv	0.099	0.008	0.90	(ii) ~ cpvrela*cpvnove*cpvcont*cpvp ers* ~ cpvenjo* ~ cpvexpe*cpvexce*cpvconv	0.547	0.07	0.78
(iii)cpvnove*cpvcont*cpvpers* ~ cpvenjo* ~ cpvexpe*cpvexce*cpvconv	0.197	0.009	0.97	(iii) ~ cpvrela*cpvnove*cpvcont*cpvpers *cpvenjo*cpvexpe*cpvexce*cpvconv	0.51	0.06	0.76
(iv)cpvnove*cpvcont*cpvpers*cpvenjo *cpvexpe*cpvexce*cpvconv	0.743	0.008	0.99				
				Solution coverage:0.674788			
Solution coverage: 0.868166				Solution consistency: 0.743678			
Solution consistency: 0.973442							

RC Raw coverage, *UC* Unique coverage, *C* Consistency; *cpvconv* convenience, *cpvexce* excellence, *cpvexpe* experience, *cpvenjo* enjoyment, *cpvpers* personalization, *cpvcont* control, *cpvnove* novelty, *cpvrela* relational benefit

negation model ~ rq = f (pv). As per extant literature, a consistency threshold of 0.8 was used to analyze the solutions (Pappas & Woodside, 2021). The overall solution consistency and coverage for the model rq = f (pv) (left-hand side of Table 6) is 0.97344 and 0.868166 respectively, which exceed the threshold values. Hence configurations of 'pv' (positive value) conditions facilitate 'relationship quality' in this study. It is noted that the first configuration (cpvrela, cpvnove, cpvcont, cpvpers, cpvexce, cpvconv) consists of all the necessary conditions of 'relationship quality' (Table 6) with a consistency and raw coverage of 0.99 and 0.838 respectively. This is the most desirable configuration, and it is indeed a *necessary and sufficient* configuration to facilitate relationship quality. This is a unique finding of this study and adds immensely to the literature. It is observed that overall solution consistency for the model ~ rq = f (pv) (negation of relationship quality, right-hand side of Table 6) is 0.743678, which is less than the threshold value of 0.8 in this study. However, the first configuration (~ cpvrela, ~ cpvnove, cpvpers, ~ cpvenjo, ~ cpvexpe, cpvexce, ~ cpvconv) has a consistency of 0.93 with reasonable raw coverage of 0.438. This configuration suggests that with increased personalization (cpvpers) and excellence (cpvexce) combined with decreased relational benefit (cpvrela), decreased novelty (cpvnovel), and decreased enjoyment (cpvenjo), decreased experience (cpvexpe) and decreased convenience (cpvconv) will reduce the level of relationship quality. It is noted that personalization (cpvpers) and excellence (cpvexce) are necessary conditions to facilitate relationship quality. But they will only facilitate the outcome if positive values are present too. This should act as an eye-opener for the management about the role of a necessary condition.

Table 7 presents various configurations obtained from the truth table analysis as per the model rq = f (nv) and its negation model ~ rq = f (nv), that is what configurations of the negative value antecedents may facilitate or impede the relationship quality. It is observed that overall solution consistency and coverage are above the threshold values for the model rq = f (nv) (left-hand side of Table 7). This analysis offers

Table 7 Configurations as per model rq = f (nv) and ~ rq = f (nv)

Configurations of negative values (nv) for predicting high scores of relationship quality	RC	UC	C	Configurations of negative values (nv) for predicting low scores of relationship quality	RC	UC	C
Model: rq = f (nv)				Model: ~ rq = f (nv)			
Configurations:				Configurations			
(i) cnveffo	0.972	0.783	0.899	(i) ~ cnvpriv*cnveffo	0.80	0.13	0.63
(ii) ~ cnvsecu*cnvperf* ~ cnvpriv	0.19	0.002	0.877	(ii) ~ cnvsecu*cnvperf* ~ cnvpriv	0.71	0.03	0.75
Solution coverage: 0.973499				Solution coverage:0.838259 Solution consistency: 0.637458			
Solution consistency: 0.892807							

RC Raw coverage, *UC* Unique coverage, *C* Consistency; *cnveffo* effort, *cnvperf* performance risk, *cnvsecu* = security, *cnvpriv* = privacy two configurations. Configuration (i) has only one antecedent condition of cnveffo (effort) with consistency and coverage of 0.899 and 0.972 respectively. Hence, it will significantly facilitate relationship quality. It is noted that effort is also a necessary condition to impede relationship quality, albeit with low relevance (see Table 5). Hence, this study suggests that cnveffo (effort) needs to be managed carefully as it is a necessary condition to impede relationship quality but a sufficient condition to facilitate the same. The 2nd configuration for the model rq = f (nv) is ~ cnvsecu, cnvperf, ~ cnvpriv has a consistency of 0.877, but low coverage of 0.19. Therefore, this configuration is not very relevant or important because of low coverage.

Table 7 (right-hand side) also shows that overall solution coverage for the model ~ rq = f (nv) is quite high (0.838), hence highly relevant. However, the solution consistency (0.637) is below the threshold. Literature suggests that (Ragin, 2008) consistency is like 'significance' in a statistical sense. Thus, it can be concluded that there are no significant configurations of the negative values (nv) to impede relationship quality seriously.

Table 8 presents various configurations obtained from the truth table analysis as per the model rq = f (pv, nv) and its negation model ~ rq = f (pv, nv), that is what configurations of positive and negative value antecedents may facilitate or impede the relationship quality. The right-hand side of Table 8 shows that overall solution coverage and consistency (0.56155 and 0.5796) are below the threshold values. Hence, there are no configurations of pv and nv which will significantly impede relationship quality. However, solution coverage and consistency of the model rq = f (pv, nv) (left-hand side of Table 8) are 0.760 and 0.9956 respectively and above the threshold values. This analysis produces five configurations with very high consistency values. However, only configurations (ii) and (iii) have reasonable coverages of 0.644 and 0.702 respectively (Table 8). It is noted that configurations (ii) (cnvperf, cnvpriv, cnveffo, cpvrela, cpvnove, cpvcont, cpvpers, cpvenjo, cpvexce, cpvconv) and (iii) (cnvpriv, cnveffo, cpvrela, cpvnove, cpvcont, cpvpers, cpvenjo, cpvexpe, cpvexce, cpvconv) contain all the necessary conditions of pv values to facilitate relationship quality (Table 4). This shows the significance of the necessary conditions and management should do their utmost to manage these conditions carefully.

4.7 Test of Predictive Validity

Test of predictive validity is very important in fsQCA. Achieving a good model fit (in terms of consistency and coverage) does not ensure that the configurations offer good predictions. Predictive validity shows how configurations obtained from one sample hold very nicely for additional samples in terms of consistency and coverage (Pappas & Woodside, 2021; Woodside, 2013).

Table 8 Configurations as per model rq = f (pv, nv) and ~ rq = f (pv, nv)

Configurations of positive and negative values (pv, nv) for predicting high scores of relationship quality	RC	UC	C	Configurations of positive and negative values (pv, nv) for predicting low scores of relationship quality	RC	UC	C
Model: rq = f (pv, nv) Configurations:				Model: ~ rq = f (pv, nv) Configurations			
(i) ~ cnvsecu*cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo*cpvexce*cpvconv	0.265	0.008	0.999	(i) ~ cnvsecu*cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo* ~ cpvexpe*cpvexce*cpvconv	0.493	0.002	0.665
(ii)cnvperf*cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo*cpvexce*cpvconv				(ii)cnvperf*cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo* ~ cpvexpe*cpvexce*cpvconv			
(iii)cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo*cpvexpe*cpvexce*cpvconv	0.644	0.008	0.996	(iii)cnvsecu* ~ cnvperf*cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers* ~ cpvenjo* ~ cpvexpe*cpvexce*cpvconv	0.486	0.011	0.708
(iv) ~ cnvsecu* ~ cnvperf*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo*cpvexpe*cpvexce*cpvconv	0.702	0.031	0.996	(iv) ~ cnvsecu* ~ cnvperf* ~ cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo*cpvexpe*cpvexce*cpvconv			
(v)cnvsecu* ~ cnvperf*cnvpriv*cnveffo*cpvrela*cpvnove*cpvcont*cpvpers* ~ cpvenjo* ~ cpvexpe*cpvexce*cpvconv	0.193	0.009	0.998	Solution coverage:0.56155 Solution consistency: 0.5796	0.453	0.016	0.746
Solution coverage: 0.760							
Solution consistency: 0.9956	0.141	0.013	1.00		0.456	0.037	0.781

RC Raw coverage, *UC* Unique coverage, *C* Consistency; *cpvconv* convenience, *cpvexce* excellence, *cpvexpe* experience, *cpvenjo* enjoyment, *cpvpers* personalization, *cpvcont* control, *cpvnove* novelty, *cpvrela* relational benefit, *cnveffo* effort, *cnvperf* performance risk, *cnvsecu* security, *cnvpriv* privacy

Table 9 Configurations as per model rq = f (pv) for the subsample

Configurations of positive values (pv) for predicting high score of relationship quality for the subsample	Raw coverage	Unique coverage	Consistency
(i) cpvrela*cpvnove*cpvcont*cpvpers*cpvenjo*cpvexce*cpvconv	0.799922	0.054729	0.993711
(ii)cpvrela*cpvnove*cpvcont*cpvpers*cpvexpe*cpvexce*cpvconv	0.751793	0.016278	0.996432
(iii)cpvnove*cpvcont*cpvpers*cpvenjo*cpvexpe*cpvexce*cpvconv	0.744872	0.009613	0.995802
(iv) ~ cpvrela* ~ cpvnove* ~ cpvcont*cpvpers* ~ cpvenjo* ~ cpvexpe*cpvexce* ~ cpvconv	0.089849	0.005768	0.926024
(v) ~ cpvrela*cpvnove*cpvcont*cpvpers* ~ cpvenjo* ~ cpvexpe*cpvexce*cpvconv	0.159895	0.019418	0.982670

Solution coverage: 0.858368

Solution consistency: 0.981893

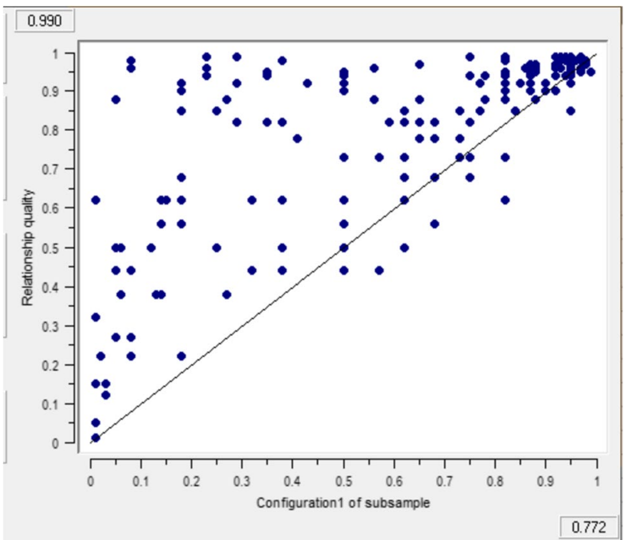

Fig. 2 Fuzzy-plot of configuration 1(from Table 9) using data from the holdout sample

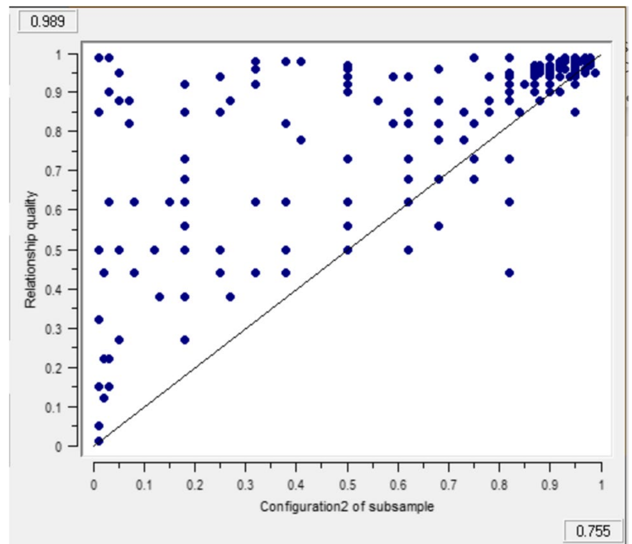

Fig. 3 Fuzzy-plot of configuration 2 (from Table 9) using data from the holdout sample

To test predictive validity, we have followed the extant literature (Pappas & Woodside, 2021; Woodside, 2013). We first divide our original sample randomly into a subsample and a holdout sample. The complete fsQCA is then run using the subsample. The configurations obtained from the subsample are then tested for consistency and coverage using the holdout sample. As long as the configurations of the subsample hold true (i.e., exceeding the threshold values of consistency and coverage) for the holdout sample the predictive validity is maintained. The threshold values for consistency and coverage, for both samples, are chosen as discussed before in Section 5.6 in the case of original fsQCA analysis. In this study, the sample was randomly divided and tested all the models described earlier. The partial test result for the model rq = f (pv) is presented below.

Table 9 shows various configurations obtained from the subsample. It is noted that the solution consistency (0.98) and coverage (0.85) are very good. Configurations (i) – (iii) are good for both consistency and coverage.

The results for testing the validity of configurations (i) and (ii) are shown. To test the validity, the configurations (i) and (ii) are first created as new variables in the holdout sample using the function *fuzzy and (x,…,).* The new variables are then plotted against the outcome (relationship quality) using the holdout sample. Figures 2 and 3 show these plots. It is observed that the configurations obtained from the subsample also show high consistency and coverage for the holdout sample. For configuration (i), the consistency is 0.99 and the coverage is 0.77 (Fig. 2). For configuration (ii), they are 0.989 and 0.756 respectively. Tests of other models and configurations also show high consistency and coverage. Hence, the predictive validity of the fsQCA is justified.

5 Discussions and Implications

Drawing from prior research on customer-perceived value and SET (in a customer-service robot interaction context), this study formulates value configurations that facilitate or impede high-quality relationships between customers and service robots in the context of Industry 5.0. This study corroborates earlier researchers' work that recognizes the simultaneous influence of factors resulting in "the influence-to-outcome relationship" (Smith et al., 2013, p. 1157; see also, Kim et al., 2022; Hlee et al., 2023).

5.1 Analysis of the Configurations and Test of the Propositions

This study has integrated eight positive values (relational benefit, novelty, control, personalization, enjoyment, experience, excellence, convenience), four negative values (security, performance concern, privacy, effort required), and a combination of positive and negative values in the context of Industry 5.0. The analysis revealed some important findings, which are as follows. The necessary analysis revealed that the integration of six positive values (relational benefit, novelty, control, personalization, excellence, convenience) are significant necessary conditions (consistency > 0.90 and coverage > 0.90) to facilitate relationship quality (Table 4). The sufficiency analysis also revealed that the configuration of these six conditions is also sufficient to produce high relationship quality (Table 6, configuration (i). Hence, the configuration of *relational benefit, novelty, control, personalization, excellence,* and *convenience* are both necessary and sufficient conditions to facilitate relationship quality in the context of Industry 5.0. However, this configuration of positive values disregards the influence of the negative values. Literature suggests that value should be treated as a tradeoff including both benefits and costs (Leroi-Werelds, 2019).

Integrating perceived values and moving towards value-driven robots in the context of Industry 5.0 and their analysis of the combination of positive and negative values revealed two significant configurations (see configuration (ii) and (iii) in Table 8). Both configurations facilitate the relationship quality between customers and service robots. In both of these configurations, the necessary and sufficient positive values are present along with two negative values of *privacy* and *effort*. Thus, a new configuration of the positive values of *relational benefit, novelty, control, personalization, excellence,* and *convenience* and the negative values of *privacy* and *effort* were tested separately which was consistent and covered 0.91 and 0.67, respectively. produced a consistency and coverage of 0.91 and 0.67 respectively. Thus, this configuration of integrating perceived values (*relational benefit, novelty, control, personalization, excellence, convenience, privacy, and effort)* and moving towards value-driven robots is also highly effective in enhancing the relationship quality.

The preceding discussion supports Proposition 1 which implies that the presence of both positive and negative values is a prerequisite condition to predict the relationship quality of human–robot interactions in a retail setting. The result also empirically validates Moliner et al., (2007) and later Leroi-Werelds (2019) value conceptualization of accumulated value with both positive and negative components. It also echoes prior studies that identified value components as antecedents for relationship quality (Wisker, 2020). It moves towards considering value-driven dynamics and long-term service to humanity within the planetary boundaries of Industry 5.0 (Breque et al., 2021).

The analysis of this study shows that there are no necessary conditions of negative values with acceptable consistency to impede high-quality relationships between customers and service robots in integrating perceived values and moving towards value-driven robots (Table 5). The sufficiency analysis also shows that there is no configuration of negative values to impede the high-quality relationship between customers and service robots in integrating perceived values and moving towards value-driven robots (Table 7). The study results show that there are no specific configurations of positive and negative values that significantly impede relationship quality (Table 8). The results show that *personalization* and *excellence* are necessary conditions to facilitate relationship quality and move towards value-driven robots. However, they will not facilitate the outcome when there exists a lower level of (negation) other positive values, namely, *relational benefit, novelty, control and convenience* (configuration (i), Table 6). Thus, it can be concluded that integrating negative values alone or in combination with positive values does not impede high relationship quality. The lower level (negation) of the positive values does impede the relationship quality adequately. This does not support Proposition 2 which suggests that the presence of both positive and negative values only facilitates relationship quality but does not impede it. Hence, it can be argued that integrating lower levels of positive values is important in the formation of perceptions towards high-quality relationships of value-driven robots in the context of Industry 5.0. The lower levels of positive values generate an impression in customers' minds which stays for a long time and may affect relationship quality (Berkowitz, 2014). Thus, it can be concluded that the absence of negative values may not necessarily impede relationship quality. However, the presence of positive values (even at lower levels) is an absolute necessity for higher relationship quality between customers and service robots.

5.1.1 Customer Effort

The analysis of this study unearthed some interesting findings about *customer effort*. Necessary analysis of the integration of negative values revealed that *effort* is the most significant necessary condition that hinders the relationship quality with high consistency (> 0.9; Table 5). The sufficiency analysis also revealed *effort* (if managed well) is a sufficient condition to facilitate relationship quality (configuration (i), Table 7). This is an interesting finding and highlights the dual role of *effort* in hindering (when no effort is extended) or enhancing (when more effort is extended) relationship quality. It also supports the existing literature that studied the role of *customer effort* in value cocreation (Gruner & Soutar, 2021; Sweeney et al., 2015). Customers' perceived effort is the mental energy necessary to make sense of information environments, including technology-supported retail ones (Leroi-Werelds, 2019; Mani & Chouk, 2018). The results imply that an optimum level of mental effort exists (though less is often more) to make the most of a robot-based service interaction. Therefore, the often-entertaining nature of interacting with service robots makes customers more resilient to some level of cognitive effort (this is an interesting, little-explored association in the literature (Roy et al., 2021). Customers usually develop a positive attitude if their interaction with the technology accrues higher gains than their efforts and vice versa (Evanschitzky et al., 2015). Thus, customer effort needs to be managed judiciously.

5.1.2 Towards a Configurational Theory: How Integration of Perceived Values (Positive and Negative) Influence Relationship Quality in the Context of Industry 5.0

The basic premise of this study is that the relationship quality of human–robot interactions is a complex phenomenon. Complexity, causal complexity, and configurations have been studied widely (e.g., Byrne, 2005, Furnari et al., 2021 and Misangyi et al., 2017; among many others). Several studies have also suggested that there are connections among them; for instance, Byrne (2005) suggests that configurations help to understand the complexity and causal complexity adequately in a problem domain. Misangyi et al. (2017) stress that configurations effectively represent causal complexity. The authors also outline the fundamental elements of the configurational view, leading to the development of a configurational theory of a problem domain, which necessitates the use of fsQCA for data analysis. Based on the above and discussions, this study theorizes the relationship quality of customer-service robot interactions in the context of Industry 5.0 as follows:

(i) Configurations and integration of the antecedents of high levels of positive perceived values are *necessary and sufficient* conditions to facilitate relationship quality between customers and service robots in their long-term service to humanity within the planetary boundaries (Industry 5.0) and they do not impede the customer service robot relationship quality in this context.

(ii) Configurations and integration of the antecedents of high levels of positive perceived values (both positive and negative) also facilitate relationship quality between customers and service robots in their long-term service to humanity in the context of Industry 5.0 and they do not impede the customer-service robot relationship quality.

(iii) Lower levels of positive values impede relationship quality.

(iv) Customer effort plays a dual role. It may either impede or facilitate relationship quality between customers and service robots in its long-term service to humanity, depending on how well it is managed to interact with the robot.

5.2 Theoretical and Managerial Contributions

To date, research offers limited insights into how diverse sets of values delivered through technological innovations like service robots—impact the quality of relationships (Zeithaml et al., 2020). With this in mind, our study's primary contribution lies in identifying specific combinations of values that either facilitate or obstruct the development of high-quality relationships between customers and service robots within the context of Industry 5.0. In this burgeoning and significant context, our research recognizes the intricate trade-offs associated with individual value categories. Our focus is on uncovering the intricate patterns of value integration by exploring various combinations of positive and negative values.

Rather than solely examining isolated values that affect relationship quality, this research substantiates the concept of *value recipes* (Leroi-Werelds, 2019). These are distinctive combinations of positive and negative values that have the potential to impact the quality of interactions between customers and service robots. Specifically, the study adopts Leroi-Werelds's (2019) value typology, which offers an advanced framework for understanding value within technological advancements and the adoption of service robots in business environments. Broadly speaking, our work thus extends Leroi-Werelds's study (2019) on the changing face of customer value in fast-moving digital marketing environments. More specifically, our typology complements Novak and Hoffman's (2019) object-centered approach, which acknowledges the varying levels of agency, autonomy, and authority exhibited by service robots and underscores the importance of considering these attributes (see also Canniford & Bajde, 2016).

In addition to the value typology, this study grounds its propositions in social exchange theory, which helps define and characterize the reciprocal interaction between customers and service robots (Blau, 1964). As a corollary, by integrating positive and negative values into a single model, the study unveils antecedents that facilitate, or stand in the way of, a high-quality relationship between customers and service robots.

Further, this study builds upon prior research that investigates the role of functional, social, emotional, novelty value, and relational values in establishing relationship quality (e.g., Dorai et al., 2021; Ulaga & Eggert, 2006). What sets this study apart from this related research in the field (e.g., Itani et al., 2019; Moliner, 2009) is that it goes beyond considering positive values in determining their impact on relationship quality. Instead, this study contributes to the literature, particularly in the domain of service robots, by identifying various *value recipes* consisting of both positive and negative values arranged in different configurations that prove effective in enhancing the relationship quality between customers and service robots. Also, the results highlight those negative values, either on their own or in conjunction with positive values, do not impede relationship quality.

From a practical standpoint, the findings suggest guidelines for successfully infusing the retail landscape with more intelligent technologies, including service robots. Our work not only confirms the importance for managers to better understand their customers, including their perceived value configurations, but also robots' potential to foster high-quality relationships with their human customers. The interplay of many positive values, such as personalization and convenience, is essential for a solid, value-enhancing relationship between customers and robots. However, negative values, such as effort and privacy concerns must be considered too. Taken together, these findings are of practical value for managers who wish to make the most of their investments in robots, particularly in a retailing context.

Interestingly, we also found empirical support for the notion that customers' cognitive effort plays a key role in determining how much they benefit from interactions with robots. This finding not only confirms prior work that found cognitive costs essential for customers to derive value from interactions with companies (e.g., Gruner & Soutar, 2021) but also cautions managers to prioritize frictionless customer journeys over more complex technology-infused ones.

6 Limitations and Future Research

This study carries some limitations. First, the study participants come from a single country i.e., the United States of America, which limits our results' generalizability. Prior studies have shown variations in consumer perception and evaluation of service robots across cultures. For example, Americans demonstrate greater likeability for robots with humanlike optics, whereas the Japanese express the opposite preference (Bartneck, 2008). Also, it has been shown that consumers from cultures with higher individualism and masculine ratios are less likely to use and benefit from service robots (Li et al., 2010). Hence, future research should consider how cultural background influences customer-perceived value from service robots and its influence on relationship quality.

Second, this study considers Leroi-Werelds (2019) value typology (positive vs. negative) representing the positivist paradigm as the antecedent of relationship quality. Future research should consider the conceptualization of customer-perceived value from other paradigms such as interpretive and social constructionist (Zeithaml et al., 2020), and examine its role in determining commonalities (vs. deviations) in developing relationship quality with service robots.

Third, our findings are limited to the context of tangible robots delivering services targeted at people's possessions. Since other forms of robots (virtual robots) have different characteristics (Wirtz et al., 2019), future research should test the findings on other forms of robots delivering different types of tasks to generalise the findings.

Fourth, the data were gathered before the COVID-19 pandemic. It is plausible that the pandemic has altered customers' perceptions of service robots. Future studies may examine how situational (e.g., perceived health risks and self-protective behavior) and psychological factors (e.g., stress and depression) linked with the pandemic change customer-perceived value towards service robots and its impact on relationships in the context of Industry 5.0.

Appendix 1

Research Scenario (adapted from Kim et al., 2022**)**

Description of service 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:

Service robots are designed to independently deliver customer service. Service robots are system-based autonomous and adaptable interfaces that interact and communicate with customers in a human- like way through speech interactions complimented with gestures and facial expressions. Service robots can recognise social circumstances and revert according to human social norms. Service robots are increasingly adopted in retail. For example, a service robot could assist customers in locating products in an given grocery store, as well as an engagement with service robot cashier. An example of service robots in retail is provided below:

Robot: Mitra

Video URL

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

Appendix 2

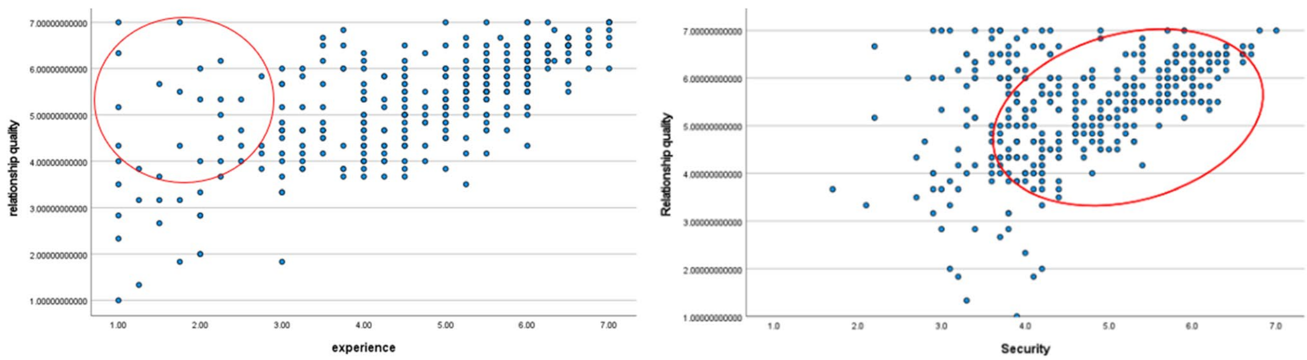

Fig. 4 Asymmetric relationship between variables. Experience is a positive value. Hence for higher values of experience, relationship quality will be high. However, the figure shows for low values of experience, relationship quality is also significantly high (shown in circle). Hence an asymmetric relationship exists. Security is a negative value. Hence for higher values of security, relationship quality will be low. However, the figure shows for high values of security, relationship quality is also high (shown in circle). Hence a significant asymmetric relationship exists

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Data Availability An anonymous survey was conducted using an online portal. Hence, participant consent is not needed/relevant.

The data that support the findings of this study are not publicly available. The data are, however, available from the authors upon reasonable request.

Declarations

Ethics Approval Approval from the University of Western Australia Ethics Committee was obtained for this research.

Consent to Participate An anonymous survey was conducted using an online portal. Hence, participant consent is not needed/relevant.

Consent for Publication An anonymous survey was conducted using an online portal. Hence, participant consent is not needed/relevant.

Competing Interests An anonymous survey was conducted using an online portal. Hence, participant consent is not needed/relevant.

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Dr Sanjit K. Roy is Professor of Marketing and Service Science and the Vice Chancellor's Professorial Research Fellow at Edith Cowan University. He is a certified LEGO® SERIOUS PLAY® Facilitator. He is an Associate Editor at European Journal of Marketing and Australasian Marketing Journal and on the editorial boards of International Journal of Information Management, Journal of Business Research, Journal

of Services Marketing, Journal of Strategic Marketing, and Journal of Service Theory & Practice. His research interests include Customer Experience Management, Impact of New Technologies (i.e., AI, robotics) on Services, and Consumer Brand Relationships. He has published in British Journal of Management, Industrial Marketing Management, European Journal of Marketing, Journal of Business Research, Journal of Marketing Management, International Journal of Information Management, Information Systems Frontiers, Internet Research, Journal of Services Marketing, among others.

Dr Gaganpreet Singh is Associate Professor at the O.P Jindal Global University, India. He has published in Journal of Business Research, Journal of Marketing Management, Journal of Strategic Marketing, Australasian Marketing Journal, Australasian Journal of Information Systems, Benchmarking: An International Journal, Journal of Fashion Marketing and Management, Journal of Revenue and Pricing Management, and Journal of Marketing for Higher Education. He has published case studies with Ivey Publishing are among the global best sellers. He has coauthored a book on primary case studies published by Pearson Education. He is the recipient of an early career scholarship from Australia New Zealand Marketing Academy (ANZMAC). He has also received several case studies writing grants from UNSW, Australia.

Dr Richard L. Gruner is Associate Professor at the University of Western Australia, and Adjunct Associate Professor at Curtin University. Richard has several awards for his research, reviewing, and teaching. His work has been published in leading international journals, such as Journal of the Academy of Marketing Science, Information Systems Journal, International Journal of Operations and Production Management, Journal of Product Innovation Management, Renewable and Sustainable Energy Reviews, Journal of Supply Chain Management, and International Journal of Management Reviews. Richard is also a regular contributor to executive teaching programs, and he serves on the editorial boards of Industrial Marketing Management, International Journal of Operations and Production Management, and International Journal of Management Reviews.

Dr Bidit L. Dey is a Reader in Marketing and Associate Head of Brunel Business School (Strategy and External Relations). Bidit's research is underpinned by his passion to study communities and cultures. He coined and theorised a new concept called 'digital consumer culture', introduced a multi-dimensional perspective toward studying acculturation, and developed a novel model of co-creation in emerging economies. Bidit has published more than 35 articles in leading business and management journals, such as: British Journal of Management, Journal of World Business, International Marketing Review; Industrial Marketing Management, Technological Forecasting and Social Change, Journal of Business Research, Information Technology and People; Information Systems Frontier; Journal of Marketing Management and Production, Planning and Control. Bidit guest edited special issues for leading management and marketing periodicals including Technological Forescasting and Social Change and Journal of Marketing Management. Bidit co-edited a monograph for Palgrave Macmillan: ICTs in Developing Countries: Research, Practices and Policy Implications, and also published book chapters and presented more than twenty-five papers in peer reviewed conferences.

Dr. Saadia is an early career academic at Curtin University, Perth in Western Australia. Her research interests lie in the areas of consumer psychology and behavior. Saadia is passionate about researching on customer life stages and consumption value, Social connectedness and wellbeing, Leisure and tourism for ageing consumer and diversity and ageing. She looks forward to collaborate with organizations and industry bodies for bringing any meaningful changes in the lives of older people. She has published in journals such as Australian Journal of Information Systems, Tourism Analysis and Journal of Cleaner Production.

Dr Syed Sardar Muhammad is an experienced educator and he has worked in higher education for 22 years. He is a senior lecture at Brunel University. His professional experience includes as an academic lead, head of studies, programme director and a director of studies. He has worked at the major academic institutions such as Brunel University London, Middlesex University London, Glasgow Caledonian University London, University of Stirling London, The University of Law Business School, Greenwich School of Management London, Global University System London, Grenoble Ecole de Management and Em Normandy Oxford. During his two-decade long career in higher education, Syed undertook a number of senior management roles including an Academic Lead, Head of Studies, Director of studies and Director programmes. He has been instrumental in leading learning and teaching enhancement and assessment standard activities providing leadership and support for programmes, teams and individuals for the enhancement of Learning and Teaching across different departments and business schools. He teaches on the Masters' and undergraduate programmes and he supervises both undergraduate and postgraduate research students. Syed is a Senior Fellow of Higher Education Academy and is member of the leading professional bodies such as Chartered Management Institute, Association of Masters of Business Administration, British Academy of Management, and Academy of Marketing. He has been instrumental in Strategy, Marketing and Entrepreneurship. Syed's research is interdisciplinary and focusses on technological innovations, digital footprints, big data, digital marketing, digitalization and privacy and security etc. His research has a particular focus on digital future, interaction with cutting edge technological platforms, adaptation and dark side behaviour of IOT/AI etc. His research output has contributed to strategy and consumer behaviour, brand reshoring, digital and social media marketing and privacy and security on digital platforms.

Mohammed Quaddus is Professor with the School of Management and Marketing, Curtin University, Perth. He has published over 300 papers in refereed journals, international conferences, and book chapters. His publications have appeared in Omega, the International Journal of Production Economics, the European Journal of Information Systems, Decision Support Systems, Supply Chain Management –An International Journal, Information Systems Frontiers, and Rural Sociology. His research interests include multiple disciplines, behavioral modeling in marketing and tourism, ICT and tourism, sustainability and tourism, information systems planning, logistics and supply chain management, and risk management in the supply chain. He successfully supervised over 60 Ph.D. students.