Instrument Development for *R*-Service Quality: A Literature Review

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Abstract

Motivated by a paucity of knowledge on the measurement of robotic service (r-service) quality, the current study strives to review the existing literature on r-service quality, with a focus on the potential methodological issues of developing measurement instruments and identifying the dimensionality of r-service quality. With a content analysis of 55 articles, this study identifies several methodological limitations of existing studies in developing measurement scales of r-service quality. This review reveals that dimensions of r-service quality are prone to be contingent on specific contexts of service industry and service type. Several common dimensions regarding evaluating r-service are identified, including tangibility, responsiveness, reliability, empathy, assurance, ease of use/usability, usefulness, anthropomorphism, perceived intelligence, and social presence. This study is the first systematic literature review on r-service quality dimensionality.

1. Introduction

Robotics and artificial intelligence (AI) have emerged in service sectors in recent years, resulting in a rapid rise of *r*-service. *R*-service refers to the service delivered by a robot [1]. Service robots are defined as "*system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers*" [2, p. 909]. Service robots can be virtual or with a physical presence [3]. Generally, virtual robots, e.g., chatbots, are used in *e*-service, whereas robots with a physical presence are deployed in offline service contexts. The service robot market is snowballing and projected to grow at a compound annual growth rate of approximately a quarter and reach 102.5 billion USD by 2025 [4]. Such service industries as hotel [5], [6], tourism [7], [8], education [9], and restaurant [10], [11] are the early adopters of service robots. In particular, the Covid-19 pandemic has made robotics unprecedentedly relevant to service sectors, particularly hospitality, for deploying robots can keep social distance and decrease human touch [12], [13].

Robotics is predicted to profoundly change service sectors and add to an essential and integral part of future consumer experience [14], [15]. The majority of the existing literature focuses on the antecedents that contribute to consumer satisfaction and intention to use *r*-service based on the theories like SERVQUAL [11], [13], Technology Acceptance Model (TAM) [16], [17], or Social Presence Theory [18], [19]. Service robots are embedded with AI, allowing them to enter humans-preserving domains, such as contextual and bilateral interactions between robots (as regular staff) and consumers [20], [21]. Compared to conventional digital services (e.g., self-service technology), humanlike interaction and emotional elements may affect consumer responses to *r*-services, resulting in differentiated facilitators and barriers to tackle *r*-services [3]. The importance is being further emphasized to develop systematic scales concerning dimensions affecting consumers to adopt and evaluate *r*-services. Unfortunately, there is a lack of consensus on the factors affecting *r*-service quality. By instrumenting *r*-service quality, this study strives to bridge this gap.

R-service quality can be conceptualized as the extent to which a service robot facilitates efficient and effective service delivery, involving from pre- to post-delivery of *r*-service [22]. *R*-service quality plays a vital role in numerous aspects of service commerce, e.g., consumer attitudes towards the *r*-service[6], [9], [23], consumer satisfaction and loyalty [24], [25], willingness to use [3], [26], [27], intention to (re)use *r*-service [5], [7], [28], [29], recommendation intention [11], etc. In light of the apparent importance of *r*-service quality in service encounters, the achievement of superior *r*-service quality has been identified as a crucial strategy for service practitioners [13], [30]. With the advent of the AI era, *r*-service quality has been increasingly important for service success, helping service organizations sustain competitive advantage in volatile environments [13], [31]. However, the conceptualization and measurement development of *r*-service quality is at its embryonic stage [11], [30], [31].

Against this backdrop, the current study conducts a content analysis of the existing literature to examine determinants of *r*-service quality. To this end, this work reviews the existing studies on measurement models of *r*-service quality in the hope of discussing the dimensionality residing in a diversity of measurement factors. This study aims to offer insightful implications for developing instruments of *r*-service quality and for its application in commercial practice.

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Table 1. Critical Studies on Instrument Development for *r*-Service Quality						
Reference	**Research context**	**Sampling**	**Type of Service robot**	**Data analysis procedure**	**Dependent variable**	**Dimensionality**
Lin et al. [25]	Tourism guide cloud service quality	Survey (N = 336); Adult users (over 16 years old) of tourism guide cloud service	Tourism cloud services	SEM	Overall satisfaction; Loyalty	**5 dimensions**: Information Quality (6); Function quality (6); Real feedback (3); Multiple visual aids (2); Enjoyment (3)
Van et al. [27]	Service quality by human-machine interactive devices (HMI)	Open-ended interview (N = 5), senior managers or expert officials of the establishments. Survey (N = 783), tourists with chatbot-like devices experiences	AI-enabled voice assistant robots	SEM	Value for Money Enhancers by use of HMI devices; Willingness to Use HMI	**6 dimensions:** Perceived Hygienic Usability (3); Perceived Safety for Usability (3); Assurance of Secure Service (2); Individualistic Involvement (3); Tangibility Associated with the Hygienic Service (3); Empathetic Secure Service and Update Information Sharing (3)
Chiang and Trimi [13]	Service quality provided by robots in hotel setting	Survey (N = 201); guests of Chase Walker Hotel who used the robotic service	Hotel service robots	Importance performance analysis	Service quality	**5 dimensions:** Tangibles; Reliability; Responsiveness; Assurance; Empathy
de Kervenoael et al. [5]	Service quality provided by social robots in hospitality services	Semi-structure interview (N = 5), hospitality managers. Survey (N = 443), consumers with robots using experience	Social robots in hospitality services	SEM	Intention to use social robot	**7 dimensions:** Empathy (3); Information Sharing (2); Perceived Usefulness (3); Perceived Ease of Use (3); Service Assurance (2); Personal Engagement (3); Tangibles (4)
Morita et al. [11]	Robotic service quality of a multi-robot cafe	Survey (N = 95), guests of the multi-robot cafe at the 18th Yagami Festival of Keio University	Service robots in cafe	Bayesian network	Intention to revisit/recommend the robot café; Customer satisfaction	**7 dimensions:** Tangibles (3); Reliability (2); Responsiveness (1); Assurance (4); Empathy (1); Interactivity (2); Entertainment factor (8)
Choi et al. [31]	The service quality perceptions of human-robot interaction	Focus-group interview (N = 16), hotel managers. Experiment (N = 339), hotel guests	Service robots in hotel	EFA; one-way ANOVA	Perceived service quality	**3 dimensions:** Interaction quality (7); Outcome quality (6); Physical service environment (2)
Yu [32]	Service quality of hotel *r*-service	Experiment and survey (N = 233), hotel guests	Humanlike service robot	Three-way ANOVAs	Service quality	**4 dimensions:** Responsiveness; Reliability; Assurance; Empathy
Park and Kwon [9]	Service quality provided by educational service robots	Survey (N = 609), Teachers in kindergartens and elementary schools, Parents, Researchers in the education field and robotic field, etc.	Teaching assistant (TA) robots	SEM; CFA	Intention to use	**5 dimensions:** Perceived enjoyment (4); Service quality (3); Perceived usefulness (4); Perceived ease of use (4); Attitudes (3)
Sohn and Kim [33]	Robot Utilization Expectation Index	Survey (N = 102); majority are students with potential roles in robot utilization	Intelligent robot	CFA; SEM	Robot utilization expectation	**6 dimensions:** Robot reliability (4); Robot necessity (4); Function (5); Robot environment (4); Government policy (5)
Zhong wt al. [6]	Service quality of robot hotel service	Scenario-based experiment (N = 214), online respondents	Service robots in hotel	t-test	Purchase intention	**2 dimensions:** Hotel service type (traditional vs. robot hotel service); Attitudes (6)
Wang et al. [16]	Artificial intelligence (AI) application service quality	Survey (N = 237), random respondents	Smart speaker	CFA; SEM	Behavior intention	**5 dimensions:** Perceived usefulness (3); Perceived ease-of-use (3); Perceived behavioral control (3); Subjective norm (3); Attitude (3)
Zhang and Qi [34]	Service quality of AI robotic hotel	Survey (N = 102), adult residents living in Beijing city for more than one year	AI-based service robots	t-test; one-way ANOVA; Regression analysis	Robotic service expectation	**5 dimensions**: Tangibles; Reliability; Responsiveness; Assurance; Empathy
Dou et al. [35]	Perceived Robot Personalities	Experiment (N = 15), university students	Humanoid robot (Pepper)	Factor Analysis; Multivariate Statistical Analysis	Perceived robot personalities	**2 dimensions** (experimental manipulation): Robot voice types; Robot gesture types
Kim et al. [36]	Service quality of the robot museum	Survey (N = 57), robot museum visitors	Museum robots (Genibo and Aibo)	Paired t-test	Service quality	**4 dimensions:** Reliability (2); Empathy (2); Tangibility (2); Responsiveness (2). Other factors: Sociability (3); Social attraction (intimacy, 10); Interaction (6); Social influence (5); Emotions (3); Customer loyalty (2); Customer satisfaction (3)
Kim and Lee [37]	Service quality on ubiquitous robot companion (URC) personal robot service	Survey (N = 490), Korean users who used the personal robot in their home for 4 Months	URC personal robot	EFA; CFA	Intention to use	**5 dimensions:** Tangible quality (tangibles, 7); Motion quality (responsiveness + assurance, 4); System quality (4); Perceived usefulness (7)
Blut et al. [38]	Branding effects of social robots	Experiment (N = 530), a random sample	Social robots	SEM	Brand Trust; Brand experience	**5 dimensions:** Anthropomorphism; Animacy; Likeability; Perceived Intelligence; Perceived Safety
Merkle [39]	Customer Responses to Service Robots	Experiment (N = 120), random participants	Humanoid service robot (Pepper)	ANOVA; Scheffé's Post Hoc Test	Customer satisfaction	**2 dimensions** (experimental manipulations): Service provider (Service robots vs. Frontline employees); Service situation (appropriate service vs. service failure)
Stock and Merkle [40]	Customer responses to robotic innovative behavior	Experiment (N = 132); university students	Humanoid service robot (Pepper)	MANOVA; Bonferroni post hoc test; Polynomial regression analysis	Customer satisfaction; Customer delight	**3 dimensions:** Perceived robotic innovative service behavior (ISB); Expectations; Confirmation between expected and perceived robotic ISB
Moussawi and Koufaris [28]	Service quality provided Personal Intelligent Agents	Survey (N = 232), undergraduate college students at a Northeastern university US.	Personalized intelligent software systems	CFA; SEM	Continuance of use intention	**6 dimensions:** Perceived intelligence (5); Perceived anthropomorphism (6); Perceived usefulness; Disconfirmation of expectation; Satisfaction with use; Subjective norms
Sohn et al. [41]	Massaging service quality	Experiments (N1 = 74, N2 = 64), participants recruited from MTurk	Conversational user interfaces	One-way ANOVA; PLS-SEM	Privacy concerns	**3 dimensions** (experimental manipulations): The presence of CUI; Perceived social presence; Perception of being watched
Li et al. [8]	Intelligent Advisory Service quality	Survey (N = 83), respondents recruited via emails and instant online messages on personal contact lists	Virtual Advisory Service	-	Service reuse intentions	**6 dimensions**: Communication style similarity; Perceived clarity; Perceived engagement; Perceived enjoyment; Perceived credibility; Social presence
Schuetzler et al. [18]	Responses to online conversational agents	Experiment (N = 103), students a MIS course at a public university in U.S.	Conversational agents	SEM	Perceived humanness; Partner engagement	**2 dimensions** (experimental manipulation): Conversational relevance; Social presence
Bruckes et al. [42]	Robo-advisors service quality in bank	Survey (N = 246), participants familiarized with the concept of robo-advisory.	Bank Robo-advisors	PLS-SEM	Intention to use	**4 dimensions:** Structural assurances; Trust in Banks; Perceived Risk; Initial Trust

Tussyadiaha and Parkb [14]	Hotel robotic service quality	Online survey (N = 841), random sample. Laboratory experiment (N = 32), respondents invited through personal communication in a professional network setting	Hotel service robots	PLS-SEM	Adoption intention	**6 dimensions**: Anthropomorphism; Animacy; Likeability; Perceived intelligence; Perceived security; Importance of operations
Lu et al. [3]	Service robot integration willingness (SRIW) scale	Survey (N = 1348), consumer samples in the United States	Service robots in four service industries (e.g., hotels, restaurants, airlines, and retail stores)	Hermeneutical approach; EFA; CFA; SEM; Invariance analysis	Willingness to use service robots	**6 dimensions**: Performance efficacy (7); Intrinsic motivation (6); Anthropomorphism (7); Social influence (7); Facilitating conditions (4); Emotions (5)
Ivanov and Webster [7]	Tourism service quality	Survey (N = 1003), respondents recruited via email and social media	Service robots in tourism	EFA	Use intention	**8 dimensions:** Information provision; Housekeeping; Food, beverages and guidance; Robot autonomy; Personal services; Entertainment; Bookings, payments and documentation; First and last impression
Stock and Merkle [43]	Robotic service quality	Experiment (N = 82), undergraduate and graduate students from a medium-sized university	Service frontline robots in hotel settings	t-test	Robot acceptance	**3 dimensions:** Functional component (ease of use, usefulness); Informational component (informativeness of interaction); Relational component (benevolence, user satisfaction, understanding)
Lu et al. [10]	Hotel robotic service quality	Experiment (N = 587), Consumer participants were recruited from Amazon Mechanical Turk	Service robots in a casual dining restaurant	Three-way ANCOVA	Service encounter evaluation; Revisit intentions; WOM intentions	**3 dimensions** (experimental manipulation): Physical appearance; Humanlike voice; Humanlike language style
Chan and Tung [44]	Hotel robotic service quality	Experiment 1 (N = 60), university students; Experiment 2 (N =180), participants recruited at the entrance of Tsim Sha Tsui Star Ferry Pier in Hong Kong	Hotel service robot	MANOVA	Ratings of brand experience	**4 dimensions**: Sensory (3); Affective (3); Behavioral (3); Intellectual (3)
Lee et al.[45]	Robotic service quality (the situation of service breakdown)	Scenario-based survey (N = 317), participants recruited from Amazon mTurk	Service robots	One-way analyses of variance	-	**5 dimensions:** Politeness, Competence, Trust robot, Like robots, Feel close to robots
Fuentes-Moraleda et al.[46]	Hotel robotic service quality	7994 online TripAdvisor reviews of 74 hotels	Hotel service robots	Sentiment analysis	Customer acceptance of service robots in hotel	**3 dimensions:** Functional dimension; Relational dimension; Social-emotional dimension
Lin et al. [47]	Hotel service quality	Survey (N = 605), participants recruited from Amazon mTurk	Artificially intelligent robotic device in hotel settings	CB-SEM	Willingness to Use AI Devices; Objection of Using AI Devices	**6 dimensions:** Social Influence (5); Hedonic Motivation (4); Anthropomorphism (4); Performance Expectancy (3); Effort expectancy (3); Emotion (5)
Gursoy et al. [26]	Hotel service quality	Survey (N = 439), participants recruited from Amazon mTurk	AI devices in hotel settings	CB-SEM	Willingness to Use AI Devices; Objection of Using AI Devices	**6 dimensions:** Social Influence (6); Hedonic Motivation (5); Anthropomorphism (4); Performance Expectancy (4); Effort expectancy (3); Positive emotion (5)
Choi et al. [48]	Robotic service quality	Experiment (N = 173), US adult consumers recruited via Amazon mTurk,	Service robot	ANOVA	Service encounter evaluation	**2 dimensions** (experimental manipulation): Language style (literal vs. figurative); Perceived credibility
Lin and Mattila [23]	Hotel robotic service quality	Interview (N = 30), participants recruited in tourist spots and online; Survey (N = 215), individuals over the age of 18, recruited from Qualtrics	Hotel service robot	CFA; SEM	Acceptance of service robots	**6 dimensions:** Privacy (3); Functional benefits (6); Novelty value (3); The appearance of service robot illustrations (5); Attitude (3); Anticipated overall hotel experience (4)
Lee et al. [49]	Hotel service quality	Survey (N = 494), random consumers	Hotel assistant robots	EFA; Cluster analysis; Discriminant analysis	Intention to use robot assistant hotel	**6 dimensions:** Facilitating conditions (3); Performance expectancy (4); Innovativeness (4); Social presence (5); Hedonic motivation (4); Perceived importance (5)
Tuomi et al.[50]	Hospitality service quality	Exploratory service experimentation (N = 30, prototype1; N =18, prototype 2), participants from an academic conference focused on technology and tourism in the UK	Humanoid service robots	Qualitative multi-method approach, including exploratory service experimentation, accompanied with observation, questionnaire, interview and photo-elicitation	Humanoid robot adoption in hospitality service encounters	**6 dimensions:** Contextual layer (concept and task fit); Social layer (degree of agency, locus of control); Interaction layer (tone of voice, gestures, mobility); Psychological layer (social pressure, social judgment, peer recognition); Extrinsic driver (technological progress, convenience, novelty); Intrinsic driver (more fulfilling jobs, more efficient processes, greater degree of control)
Zhong et al.[17]	Hotel service quality	Survey (N = 217), hotel guests who stayed in the rooms with service robots as the workforce.	Hotel service robots	EFA; CFA; Grouped regression analysis; SEM	Behavioral Intention	**7 dimensions:** Usefulness (4); Ease of use (2); Sentimental value (4); Self-efficiency (4); Attitude (2); Perceived value (3); Perceive behavioral control (2)
Blut et al. [51]	Robotic service quality	Literature retrieval (N = 71)	Physical robots, chatbots, and other AI	Meta-analysis	Intention to use	**8 dimensions:** Anthropomorphism; Animacy; Intelligence Safety; Ease of use; Usefulness; Rapport; Satisfaction
Chi et al. [52]	Social Service Robot Interaction Trust (SSRIT) Scale	Survey (N = 316), a customer panel was recruited through Amazon MTurk.	Social service robot	EFA	Social service robot interaction trust	**3 dimensions** (11 subdimensions): *Trustworthy robot function and design* (anthropomorphism (7), robot performance (9), effort expectancy (4)); *Propensity to trust robot* (familiarity (4), robot use self-efficacy (5), social influence (4), technology attachment (3), trust stance in technology (3)); *Trustworthy service task and context* (perceived service risk (5), robot-service fit (3), facilitating robot-use condition (3))

Notes: SEM means Structural Equation Modeling; EFA means Exploratory Factor Analysis; CFA means Confirmatory Factor Analysis; CB-SEM means Covariance-based Structural Equation Modeling; (M)ANOVA means (Multivariate) Analysis of Variance; The numbers with brackets mean the number of items of the respective construct (that can be found in the reviewed papers).

2. Literature Review

The literature retrieval was carried out in January 2021 through three databases of AIS Library, Scopus, and Web of Science. In addition, Google Scholar was used as a supplementary source of literature. These databases cover most of the current literature and are, in turn, the most consulted by academic staff from various fields of knowledge [53]. After gathering all the retrieval records, removing duplicates, and screening out unqualified papers, the final sample consists of 55 articles (see Figure 1). These studies either focus on developing an instrument for measuring *r*-service or aim at consumer responses to *r*-service. They are subjected to a comprehensive, in-depth content analysis of the key methodological aspects of developing various *r*-service quality scales and their proposed dimensions. Table 1 lists the key studies reviewed in this study.

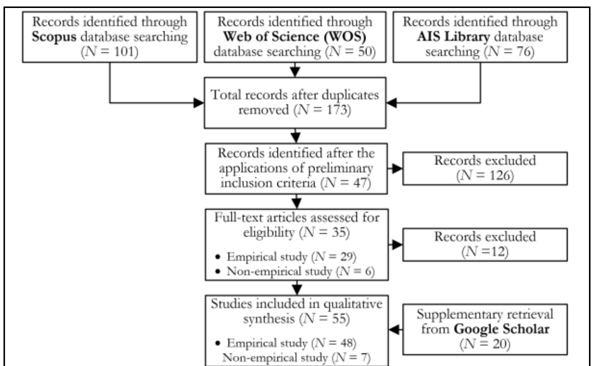

Figure 1. Flow Diagram of Literature Selection

2.1. Adequacy of dimensions

There is a lack of a widely accepted measure of *r*-service quality in the current literature. Existing *r*-service quality measures typically concerns the design of service robots and quality of service delivery, including factors triggering consumer willingness [3], [19], [47], consumer satisfaction [11], [40], [54], and/or intention to (re)use [14], [49], [51]. In this regard, Lu et al. [3] develop a six-dimensional SRIW scale: performance efficacy, intrinsic motivation, social influence, anthropomorphism, emotions, and facilitating conditions. Stock and Merkle [40] identify three constructs dominating consumer evaluation of satisfaction, i.e., perceived robotic innovative service behavior (ISB), expectations, and confirmation between expected and perceived robotic ISB. Tussyadiaha and Parkb [14] verify the determinants of consumer intention to adopt hotel service robots: anthropomorphism, perceived intelligence, and security.

In addition to the humanlike characteristics of service robots, some other scholars bend their efforts to develop more direct measures of the instruments of *r*-service quality. This research stream typically concentrates on two views: i) replicating or modifying the renowned scale dubbed SERVQUAL [55], [56]; ii) adopting technology acceptance theories, such as TAM, to develop robot-contextualized constructs [9], [16], [17].

"*SERVQUAL is a generic instrument with good reliability and validity and broad applicability*" [56, p. 445], which endorses five dominant dimensions: tangibility, responsiveness, reliability, empathy, and assurance [55]. Its principle is to assess service quality through the gap between delivered service performance and service expectations [55], [56]. A wealth of evidence shows that SERVQUAL has been verified and extensively applied in human-delivered services, e.g., hospitality and bank service [57], as well as *e*-service [58]. However, problems with SERVQUAL still arise concerning conceptualization and operationalization [57]. As proof, challenges occur to the applicable generalization of the five dimensions in different service industries because of the context-bounded attribute of service quality [57]. In respect of this, Zhang and Qi [59] apply SERVQUAL to *r*-service in hotels, and their results collapsed the five dimensions into two dimensions of tangibles and responsiveness. To evaluate service quality in the context of multi-robot café, Morita et al. [11] extend SERVQUAL dimensions from five to seven dimensions by including interactivity and entertainment factor.

A string of literature regarding *r*-service quality is established based on a consumer version of technology acceptance. According to the earliest TAM [60], perceived usefulness and ease of use are the two dominants affecting personal attitudes, thereby intention and actual behavior to use the technology. Nevertheless, the AI attributes allow service robots to gain several characteristics, such as bilateral interaction and anthropomorphism, differentiated from regular technologies (e.g., information systems) [21], [61]. This gives rise to difficulties in the applicability of the core factors from TAM or its extended theories. To address this issue, previous studies normally adopt other elements involving robot design, interactional components, and consumer emotional constructs. To illustrate, Zhong et al. [17] build an acceptance model of hotel service robots, and besides confirming the factors of usefulness, ease of use, and attitude, they also verify the significant roles of perceived value, self-efficacy, and perceived behavioral control. Stock and Merkle [43] combine TAM and role theory and developed a humanoid robot acceptance model with three dimensions: functional components (ease of use and usefulness), informational component (informativeness of interaction), and relational component (benevolence, user satisfaction, and understanding). Wang et al. [16] develop a consumer acceptance model for AI service with usefulness, ease of use, attitude, perceived behavioral control, and subjective norm.

To sum, both views mentioned above warrant further consideration. SERVQUAL is initially developed for evaluating personal-interactional services. As the saying goes, "*the definitions and relative importance of* *the five service quality dimensions change when customers interact with technology rather than with service personnel*" [62, p. 171], its dimensions might not directly transpose to *r*-service. On the other hand, a service robot is not just a regular technology but goes beyond standard technologies to enter the field preserved for human beings. This may lead to the general technology acceptance theories being inapplicable in the *r*-service context. As a result, neither SERVQUAL nor technology acceptance theories constitute a comprehensive instrument for assessing *r*-service quality. Several studies attempt to develop specific measurement scales for *r*-service quality, but without considering the overall picture of the factors introduced by different studies, which motivates and shapes the substance of this study.

2.2. Dimensionality of the *r*-service quality

Based on the content analysis of the reviewed studies, several assertions about the dimensionality of *r*-service quality can be concluded. First, there is a lack of a consensus in the construct of *r*-service quality regarding its dimensions. However, some dimensions are often considered, such as SERVQUAL five dimensions, dimensions related to technology acceptance, and robot-design characteristics. Second, several dimensions of *r*-service quality in the reviewed papers are similar with or recur from conventional service quality.

2.2.1. *R*-service quality constructs. Except for a few studies that use experimental manipulation to verify a specific single dimension [19], [63]–[65], most studies have multiple dimensional constructs for *r*-service quality, ranging from 2 [16], [48] to 11 dimensions [52]. Due to the lack of consensus regarding constructs of *r*-service quality on its dimensions, many dimensions merely appear in specific studies or research contexts. The determinants of *r*-service quality depend on involving service industries and particular service types. For example, anthropomorphism plays an essential role in service robots with physical attendance [14], [38], which is not the case for virtual robots that care more about communication patterns and language cues [63], [65]. However, some constructs, such as reliability [11], [13], [33], [59] and anthropomorphism [3], [14], [28], [38], have been frequently identified in previous studies. It is conceivable that there are several common dimensions considered by consumers when evaluating *r*-services. Ten dimensions are identified:

Reliability. As one of the five prominent dimensions of SERVQUAL, reliability is conceptualized as the capability to perform a promised service dependably, accurately, and timely [55]. Among the reviewed studies, reliability plays a significant role in general service quality [13], [32], [36], service expectation [33], and behavioral intention [11].

Assurance. In the *r*-service context, assurance refers to knowledge and courtesy of service robots and their abilities to inspire consumers' trust and confidence in receiving service cf. [55]. By reflecting service experience, assurance indicates that qualified *r*-services not only cater to particular consumer requirements but also represent safe and dependable services that are trustworthy in long-term use [5], [56]. Assurance constitutes an essential component towards customer satisfaction [11], willingness [27] or intention to use [5], [37], [42], and overall *r*-service quality [13].

Tangibility. Tangibility refers to physical facilities, equipment, and appearance of robots in *r*-services cf. [55], as one of the most common factors of *r*-service quality [66]. In the reviewed studies, tangibility is a significant dimension that determines overall service quality [13], [36], service expectations [59], and willingness [27] and intention to use robots [5], [11], [37].

Responsiveness. It refers to the willingness to help customers and offer prompt service [55]. With increasing service robots deployed to replace human personnel to delivery services, this dimension also matters in *r*-services, affecting consumer satisfaction and loyalty [24], service expectations [59], overall service quality [13], [32], [36], and intention to use [11], [37].

Empathy. Empathy can be viewed as caring and individualized attention the robotics offers for customers [55]. This dimension is relevant since service robots can mimic humans and pay attention to consumers when interacting with them [11]. In this regard, researchers report that empathy affects consumer satisfaction and loyalty [24], intention to use robots [5], [11], [37], and overall service quality [32].

Functional component. This dimension derives from a technology acceptance perspective. It is covered for that, albeit robots act as a replacement for human staff, it is essentially a novel technology that can be intimidating and complex for many individuals. *Ease of use/usability* is a reflection of consumer friendliness, whereas *usefulness* manifests ones' perception regarding the outcome of the service experience. Both play an integral part in consumers' behavioral intention [5], [9], [16], [17], [43], [51].

Anthropomorphism. It refers to that a robot is humanlike regarding either physical appearance or psychological features, such as emotions and gestures [3]. Anthropomorphism plays an essential role in affecting human-robot interaction [1] and acts as a determinant in consumer trust [38], [52], willingness to use [3], [26], [47], and intention to (re)use [14], [28], [51]. Many studies exploring the impact of anthropomorphism draw upon Uncanny Valley Theory (UVT). Some similar constructs, such as perceived humanness [18], [63], [64], physical appearance [10], [67], and uncanniness [63] can also be seen in the reviewed studies. Note, however, that the level of anthropomorphism is not necessarily linearly associated with *r*-service quality, according to UVT.

Perceived intelligence. It means consumers' perception that robots can learn, reason, and solve problems [51], [68]. Perceived intelligence concerning interacting with a service robot has been endorsed as a critical factor for accepting the robot [68], [69]. This dimension determines consumer trust [38], service robot adoption intention [14], and intention to (re)use [51].

Social presence. This dimension manifests how people react socially to robotics through psychological simulations of non-human intelligence as a real creature [15], [49]. Social presence is vital in determining behavioral intention to use service robots in hotel settings [37] and advisory services [8].

Despite that these dimensions are relatively frequently identified, they are neither necessarily generic nor exhaustive. Instruments for *r*-service quality measurement have to vary and are contingent on specific service industries and service types. In general, dimensions of *r*-service quality in the reviewed studies, except for the common dimensions mentioned above, can be subdivided into three categories: i) robot-related component, such as sociability [36], social attraction [36], autonomy [70], safety [70], animacy [69], likability [69], imitation [70], and benevolence [43]; ii) functional component, such as understanding [43], performance efficacy [3], interactivity [11][31], and scalability [70]; iii) consumer-related component, such as perceived safety [69], entertainment [11], and enjoyment [25]. Note that the common dimensions could be utilized as a starting point for instrument development of *r*-service quality.

2.2.2. Comparison with conventional service quality. While some new dimensions of *r*-service quality have been extracted, several dimensions are similar to or recur from conventional human service and *e*-service. Concretely, reliability and assurance, both prominent in the offline context of human service, are reported as top priorities of *r*-service quality [13]. The other three SERVQUAL dimensions — tangibility, responsiveness, and empathy — are also reported in several studies of *r*-service quality, e.g., [11], [13], [36]. However, mixed results exist in the reviewed literature. For instance, Zhang and Qi [59] show that tangibility and responsiveness significantly increase consumer expectations of robotic hotels, whereas the effects of reliability, assurance, and empathy are insignificant. Morita et al. [11] report the high importance of reliability and tangibility when evaluating *r*-services, while the responsiveness dimension is subscribed as low importance. The dispute may result from differentiated interpretations of these dimensions when service robots are deployed to replace human personnel. More specifically, assurance and empathy are different in the *r*-service context from its connotations in human service, since robots can always be polite and work consistently within rules to fulfill consumer needs while human staff may show extra caring attitude and go beyond rules to solve problems.

Furthermore, ease of use/usability and usefulness, which are widely used in *e*-service quality, have been adapted to *r*-service quality [5], [9], [16]. Such dimensions play important roles in evaluating *r*-service since robots can be novel technologies for many individuals, and induced unfamiliarity can intimidate them and make them feel complex to be involved in *r*-services. One issue requiring more attention is that some overlaps exist concerning connotations of SERVQUAL dimensions and ease of use/usability. Specifically, there is an intersectional area between tangibility and ease of use when considering the robot design and aesthetics.

Notably, several dimensions that are tailored for robotics, particularly humanoid robots, take essential parts in *r*-service quality. These dimensions include anthropomorphism [1], [3], [14], [26], [28], [38], [47], [51], [52], perceived intelligence [14], [28], [38], [51], social presence [8], [49], autonomy [70], animacy [69], imitation [70], etc. Past studies usually allude that human appearance tends to trigger positive perceptions and attitudes towards robots [14], [23].

2.3. Methodological issues

Studies concerning *r*-service quality utilize various methodologies, e.g., qualitative, quantitative, and hybrid methods. The first stage of establishing a measurement scale is to conduct qualitative research to identify multiple dimensions, which can be fulfilled with different qualitative approaches, e.g., the critical incident technique (CIT). CIT helps recall impressive events and identify important factors for the subject through qualitative interviews, which has proved valuable in developing service quality scales [71], [72]. Whereas some of the reviewed works use interviews to identify constructs of *r*-service quality, the application of CIT, as well as other qualitative methods, e.g., focus-group study and Delphi method, are recommended in future studies at the early stage of identifying *r*-service quality dimensions.

2.3.1. Sampling. The reviewed studies collected samples on *r*-service quality from various populations. Convenience sampling [7], [31], [44], [63] has been frequently used, whereas random sampling appear in some studies [14], [16], [38], [39]. A few studies utilize sampling of guests in real service settings, such as hospitality [13], [31], [32] and restaurants [11], [29]. Many studies recruit students in their surveys [18], [28], [40], [43].

Several research limitations exist. First, several studies obtain mainly their respondents through personal networks. Albeit recruiting respondents merely from personal networks can be more time-/effort-saving than other sampling methods, which need to fulfill specific requirements, sampling bias would be inevitable due to constraints derived from, e.g., geographical and social milieus, in particular when a representative sample is requested [73]. Second, a major limitation in the reviewed studies is that most samples are not actual consumers of *r*-services. Many respondents in the reviewed studies are recruited online. They are generally asked to self-report their perceptions of *r*-services based on reading research descriptions instead of experiencing *r*-service delivery. Respondents' perceptions of service quality with scenario descriptions may differ from experiencing *r*-service in real settings. Furthermore, pre-delivery perceptions of r-services, e.g., comfort with robots, might be more significant in physical service delivery, thus causing differences in individual perceptions for r-service quality [31]. By having respondents reflect their perceptions of *r*-services that they were not familiar with or even had not experienced, deliverables might have suffered limitations in the accuracy of findings. In this vein, the recruitment of respondents should carefully consider sample qualification to safeguard reliability in future studies. Third, many reviewed studies are based on relatively small-scale samples, which may challenge the robustness and generalization of results. In this light, samples with larger scales and more diversities should be considered in future studies.

2.3.2. Considered service industries. A vast body of the reviewed studies collects consumer data within a specific (or a type of) service sector [9], [10], [13], [36], whereas only minimal studies are across several service industries [3]. Among them, studies based on the hotel industry dominate this research stream, e.g., [13], [31]. Other specific sectors considered include, e.g., restaurant [11], [29], education [9], museum [36], household [37], tourism [8], and bank [7], [42]. Notably, Lu et al. [3] verify their instruments across four service industries: hotels, restaurants, airlines, and retails.

2.3.3. Survey administration. Both online and on-site approaches are used for data collection. Concerning qualitative research, online [23] and offline interviews have mainly been used, the latter of which includes open-ended interviews [27], semi-structured interviews [5], [24], and focus-group interviews [31]. A few studies also use literature analysis [51], [66] to identify factors impacting *r*-service quality. Regarding quantitative studies, online surveys are the most widely used by researchers. The online distribution platforms include Amazon Mechanical Turk [26], [47], [48], [52] and personal networks [8], [14], [63], [64], whereas in-person surveys are among guests in hotels [5], [13], café or restaurant [11], [29], etc. Given the importance of survey administration, the administration mode needs to be clarified in more detail. Future studies are expected to squint towards in-person surveys, particularly respondents with real experiences of *r*-service.

2.3.4. Measurement items generation. Both inductive (e.g., literature reviews) and deductive methods (e.g., exploratory research) are utilized to study *r*-service quality. Many studies strive to establish a research model to verify factors that affect behavioral intention [16], [42], [49], [51]. A few studies devote themselves to systematically developing related scales [3], [52]. Specifically, through a systematic literature review, interviews, and focus-group study, Chi et al. [52] launched a scale that measures consumer trust toward interaction with service robots. With rigorous quantitative studies, the SSRIT scale with 50 items is validated [52]. Based on a literature review and qualitative interviews, Lu et al. [3] established the SRIW scale consisting of 36 items. Moreover, in several studies, interviews are conducted among employees or managers for constructs and items generation [5], [24], [31], [74].

No consensus has been reached yet regarding the conceptualization and dimensions of *r*-service quality. Taking the dimensions of robot design as an example, some studies include communication pattern [8], [63] into robot-design constructs; others consider more the visual presence of robots, e.g., anthropomorphism [3], [14], [26], [47], [51]. The diversity of constructs in different studies underlines the lack of a consensus regarding the components of *r*-service quality. This may result from two main reasons. First, the conceptualization of the definition, scope, and dimensions of *r*-service leaves to be framed. Second, while some qualitative research relies on literature analysis and/or interview to generate constructs, a high proportion of studies directly develop research models and use data-driven approaches, e.g., EFA, to validate measurement items. In this light, future research is expected to develop a conceptual framework more specifically, comprehensively accounting for literature, expert panels, consumers, and operators. Thereby, the components of *r*-service quality, its dimensions, and scale-items can be identified and validated.

2.3.5. Dimensionality analysis. Given that many of the observed studies investigate the impact of antecedents on related dependent variables, such as behavioral intention and consumer satisfaction, a number of studies utilize SEM to test research models [5], [14], [38]. Besides, the dimensionality of the measures is examined primarily with EFA [3], [7], [17], [23], [37], [49] and/or CFA [3], [16], [17], [24], [28], [33], [37], [52], [74].

Whereas the purpose of EFA is "*to identify the factor structure or model for a set of variables*" [75, p. 10] via dropping underqualified items, its use has been challenged with its demerits, such as the nonuniqueness of the estimates accounted for factor loadings and the lack of indicators of goodness-of-fit as the case of CFA does [72]. Furthermore, the possibility in EFA that items load on more than one factor may impact the distinctiveness and interpretation of items [76]. Taking together the merits of CFA, such as allowing a comparison of different model specifications, a combination of EFA and CFA is expected in future studies.

3. Conclusion and Implications

The present study reviews the current knowledge on the instruments of *r*-service quality and contributes to i) identifying common dimensions for *r*-service quality; ii) outlining the methodology of instrument development for *r*-service quality.

This study detects heterogeneity in dimensions in the reviewed studies concerning *r*-service quality. However, several critical dimensions are identified in previous studies, including SERVQUAL five dimensions, ease of use/usability, usefulness, and three robot-related dimensions. This study demonstrates that the measurement of *r*-service quality shares several dimensions with traditional human service and *e*-service. Meanwhile, some dimensions of *r*-service quality are distinctive from conventional service settings. These distinctive dimensions focus upon social-emotional factors induced mainly by robot characteristics.

3.1. Research implications

This study offers several research implications. First, merely a few studies specifically develop and validate related measurement scales, i.e., the SRIW [3] and SSRIT scale [52]. Given a scarcity of knowledge on *r*-service quality, it calls for more studies to develop measurement scales for *r*-service quality.

Second, most of the identified common dimensions are function-oriented dimensions that reflect the service delivery process, including SERVQUAL five dimensions and ease of use/usability. However, the high dependence on these dimensions has been criticized by scholars for constituting the misspecification of service quality in both human service and *e*-service. Thus, future studies are expected to integrate other views from pre/post-delivery and reexamine the conceptualization of *r*-service quality.

Third, this study shows that more specific dimensions are contingent on particular service industries and service types. It is reasonable since different service contexts have different determinants to foster better service quality. There is no utterly generic measurement instrument of service quality, and even the widely-utilized SERVQUAL do not apply universally. Thus, a valid measurement scale of *r*-service quality for specific contexts should include service industry/type-specific dimensions as supplements for the generic dimensions. It would also be interesting to assess the weights of different dimensions across different robots in future studies.

Finally, more attention should be paid to methodological issues. Future studies should make more efforts in the methodological approaches to identifying dimensions and generating measurement items of *r*-service quality, as well as the sampling methods and size. Random and relatively bigger sample sizes across multiple service industries are warranted in future studies.

3.2 Managerial implications

These findings allow us to propose several suggestions for business practitioners designing/manufacturing/adopting *r*-services. First, considering the identification of SERVQUAL five dimensions in *r*-service quality, *r*-service managers should fully understand the keys to effective deployment of service robots: i) ensuring the delivery of promised services occur in a reliable, accurate, and timely manner; ii) having a suitable appearance (it is important to take UVT into account), equipment, and interacting skills for the specific service; iii) helping consumers actively solve problems and providing prompt service; iv) performing reliable services consistently and politely; v) paying caring and individualized attention to customers. Since *r*-services are still in an infant stage, service failures are inevitable. Under this circumstance, assistance from human staff is necessary for *r*-service delivery, particularly when consumers encounter interaction difficulties. In this vein, the possible negative perceptions induced by service failures could be alleviated.

Second, considering that several reviewed studies emphasize the importance of ease of use/usability, robot manufacturers should pay more attention to the function design of service robots to make them easier to navigate and interact with. Third, as a replacement for human personnel, robot characteristics are of significance for consumer perceptions. Consumers need to feel emotionally positive during service transactions. Thus, robot manufacturers should focus on the psychological evaluation of robots as social entities and account for social-emotional elements in robot design.

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5. References

[1] J. Murphy, U. Gretzel, and J. Pesonen, "Marketing robot services in hospitality and tourism: the role of anthropomorphism," *J. Travel Tour. Mark.*, vol. 36, no. 7, pp. 784–795, 2019.

[2] J. Wirtz *et al.*, "Brave new world: service robots in the frontline," *J. Serv. Manag.*, vol. 29, no. 5, pp. 907–931, 2018.

[3] L. Lu, R. Cai, and D. Gursoy, "Developing and validating a service robot integration willingness scale," *Int. J. Hosp. Manag.*, vol. 80, pp. 36–51, Jul. 2019.

[4] Market Research, "Service Robotics Market," *Market Research.com*, 2020. [Online]. Available: https://www.marketresearch.com/MarketsandMarkets-v3719/Service-Robotics-Environment-Type-Professional-13068761/. [Accessed: 23-Apr-2021].

[5] R. de Kervenoael, R. Hasan, A. Schwob, and E. Goh, "Leveraging human-robot interaction in hospitality services: Incorporating the role of perceived value, empathy, and information sharing into visitors' intentions

to use social robots," *Tour. Manag.*, vol. 78, no. November 2019, p. 104042, 2020.
[6] L. Zhong, S. Sun, R. Law, and X. Zhang, "Impact of robot hotel service on consumers' purchase intention: a control experiment," *Asia Pacific J. Tour. Res.*, 2020.
[7] S. Ivanov and C. Webster, "Perceived Appropriateness and Intention to Use Service Robots in Tourism," in *Information and Communication Technologies in Tourism 2019*, 2019, pp. 237–248.
[8] M. Li, J. Hou, and B. Jiang, "The Impact of Communication Style Similarity on Customer's Perception of Virtual Advisory Services: A Similarity Theory Perspective," in *Twelfth Wuhan International Conference on E-Business*, 2013, pp. 295–304.
[9] E. Park and S. J. Kwon, "The adoption of teaching assistant robots: a technology acceptance model approach," *Program*, vol. 50, no. 4, pp. 354–366, 2016.
[10] L. Lu, P. Zhang, and T. (Christina) Zhang, "Leveraging 'human-likeness' of robotic service at restaurants," *Int. J. Hosp. Manag.*, vol. 94, p. 102823, Apr. 2021.
[11] T. Morita, N. Kashiwagi, A. Yorozu, H. Suzuki, and T. Yamaguchi, "Evaluation of a Multi-robot Cafe Based on Service Quality Dimensions," *Rev. Socionetwork Strateg.*, vol. 14, no. 1, pp. 55–76, 2020.
[12] K. Matthews, "Pandemic proves utility of a wide range of service robots," *The Robot Report*, 2020. [Online]. Available: https://www.therobotreport.com/pandemic-proves-utility-wide-range-service-robots/. [Accessed: 23-Apr-2021].
[13] A. H. Chiang and S. Trimi, "Impacts of service robots on service quality," *Serv. Bus.*, vol. 14, no. 3, pp. 439–459, 2020.
[14] I. P. Tussyadiaha and S. Parkb, "Consumer Evaluation of Hotel Service Robots," in *Information and Communication Technologies in Tourism 2018*, 2018, pp. 308–320.
[15] V. W. S. Tung and R. Law, "The potential for tourism and hospitality experience research in human-robot interactions," *Int. J. Contemp. Hosp. Manag.*, vol. 29, no. 10, pp. 2498–2513, 2017.
[16] S. M. Wang, Y. K. Huang, and C. C. Wang, "A Model of Consumer Perception and Behavioral Intention for AI Service," in *MSIE 2020: Proceedings of the 2020 2nd International Conference on Management Science and Industrial Engineering*, 2020, pp. 196–201.
[17] L. Zhong, X. Zhang, J. Rong, H. K. Chan, J. Xiao, and H. Kong, "Construction and empirical research on acceptance model of service robots applied in hotel industry," *Ind. Manag. Data Syst.*, 2020.
[18] R. M. Schuetzler, G. M. Grimes, and J. S. Giboney, "An investigation of conversational agent relevance, presence, and engagement," *Am. Conf. Inf. Syst. 2018 Digit. Disruption, AMCIS 2018*, pp. 1–10, 2018.
[19] V. Yoganathan, V. S. Osburg, W. H. Kunz, and W. Toporowski, "Check-in at the Robo-desk: Effects of automated social presence on social cognition and service implications," *Tour. Manag.*, vol. 85, pp. 261–5177, 2021.
[20] S. Zhang, J. Qin, S. Cao, and J. Dou, "HRI design research for intelligent household service robots: Teler as a case study," in *International Conference of Design, User Experience, and Usability*, 2018, pp. 513–524.
[21] S. Schuetz and V. Venkatesh, "Research perspectives: The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction," *J. Assoc. Inf. Syst.*, vol. 21, no. 2, pp. 460–482, 2020.
[22] A. Parasuraman, V. A. Zeithaml, and A. Malhotra, "E-S-QUAL a multiple-item scale for assessing electronic service quality," *J. Serv. Res.*, vol. 7, no. 3, pp. 213–233, 2005.
[23] I. Y. Lin and A. S. Mattila, "The Value of Service Robots from the Hotel Guest's Perspective: A Mixed-Method Approach," *Int. J. Hosp. Manag.*, vol. 94, p. 102876, Apr. 2021.
[24] N. T. Duy, S. R. Mondal, N. T. T. Van, P. T. Dzung, D. X. H. Minh, and S. Das, "A study on the role of web 4.0 and 5.0 in the sustainable tourism ecosystem of Ho Chi Minh City, Vietnam," *Sustain.*, vol. 12, no. 17, 2020.
[25] S. P. Lin, C. L. Yang, H. C. Pi, and T. M. Ho, "Tourism guide cloud service quality: What actually delights customers?," *Springerplus*, vol. 5, no. 1, pp. 1–9, 2016.
[26] D. Gursoy, O. H. Chi, L. Lu, and R. Nunkoo, "Consumers acceptance of artificially intelligent (AI) device use in service delivery," *Int. J. Inf. Manage.*, vol. 49, pp. 157–169, 2019.
[27] N. T. T. Van *et al.*, "The role of human–machine interactive devices for post-COVID-19 innovative sustainable tourism in Ho Chi Minh City, Vietnam," *Sustainability*, vol. 12, no. 9523, pp. 1–30, 2020.
[28] S. Moussawi and M. Koufaris, "Perceived Intelligence and Perceived Anthropomorphism of Personal Intelligent Agents: Scale Development and Validation," in *Proceedings of the 52nd Hawaii International Conference on System Sciences*, 2019, vol. 6, pp. 115–124.
[29] A. Lin, E. Ma, and B. T. Chen, "The effect of interactive IT table service on consumer's Revisit intention," *Adv. Hosp. Tour. Res.*, vol. 7, no. 1, pp. 124–136, 2019.
[30] O. H. Chi, G. Denton, and D. Gursoy, "Artificially intelligent device use in service delivery: a systematic review, synthesis, and research agenda," *J. Hosp. Mark. Manag.*, vol. 29, no. 7, pp. 757–786, 2020.
[31] Y. Choi, M. Choi, M. Oh, and S. Kim, "Service robots in hotels: understanding the service quality perceptions of human-robot interaction," *J. Hosp. Mark. Manag.*, vol. 29, no. 6, pp. 613–635, 2020.
[32] C. E. Yu, "Humanlike robot and human staff in service: Age and gender differences in perceiving smiling behaviors," *2018 7th Int. Conf. Ind. Technol. Manag. ICITM 2018*, vol. 2018-Janua, no. July, pp. 99–103, 2018.
[33] S. Y. Sohn and M. J. Kim, "Strategies for revitalization for intelligent robot industry in Korea based on structural equation model," *Ind. Rob.*, vol. 37, no. 1, pp. 97–105, 2010.
[34] Y. Zhang and S. Qi, "User Experience Study: The Service Expectation of Hotel Guests to the Utilization of AI-Based Service Robot in Full-Service Hotels," in *International Conference on Human-Computer Interaction*, 2019, pp. 350–366.
[35] X. Dou, C. F. Wu, K. C. Lin, and T. M. Tseng, "The Effects of Robot Voice and Gesture Types on the Perceived Robot Personalities," in *International Conference on Human-Computer Interaction*, 2019, pp. 299–309.
[36] M. G. Kim, H. Lee, J. Lee, S. S. Kwak, and Y. Joo, "Effectiveness and service quality of robot museum through visitors experience: A case study of RoboLife Museum in South Korea," *2015 Int. Symp. Micro-NanoMechatronics Hum. Sci. MHS 2015*, 2016.
[37] Y. Kim and H. S. Lee, "Quality, perceived usefulness, user satisfaction, and intention to use: An empirical study of ubiquitous personal robot service," *Asian Soc. Sci.*, vol. 10, no. 11, pp. 1–16, 2014.
[38] M. Blut, N. V Wünderlich, and C. Brock, "Innovative technologies in branded-service encounters: How robot characteristics affect brand trust and experience," in *International Conference on Information Systems 2018, ICIS 2018*, 2018.
[39] M. Merkle, "Customer Responses to Service Robots – Comparing Human-Robot Interaction with Human-Human Interaction," in *Proceedings of the 52nd Hawaii International Conference on System Sciences*, 2019, pp. 1396–1405.
[40] R. M. Stock and M. Merkle, "Customer responses to robotic innovative behavior cues during the service encounter," in *International Conference on Information Systems 2018, ICIS 2018*, 2018, pp. 1–17.
[41] S. Sohn, T. U. Braunschweig, and S. Sohn, "Association

for Information Systems Can Conversational User Interfaces Be Harmful ? The Undesirable Effects on Privacy Concern Can Conversational User Interfaces Be Harmful ? The Undesirable Effects on Privacy Concern," 2019.
[42] M. Bruckes, D. Westmattelmann, A. Oldeweme, and G. Schewe, "Determinants and barriers of adopting robo-advisory services," in *40th International Conference on Information Systems, ICIS 2019*, 2019.
[43] R. M. Stock and M. Merkle, "A service Robot Acceptance Model: User acceptance of humanoid robots during service encounters," in *IEEE International Conference on Pervasive Computing and Communications Workshops, PerCom Workshops*, 2017, pp. 339–344.
[44] A. P. H. Chan and V. W. S. Tung, "Examining the effects of robotic service on brand experience: the moderating role of hotel segment," *J. Travel Tour. Mark.*, vol. 36, no. 4, pp. 458–468, 2019.
[45] M. K. Lee, S. Kiesler, J. Forlizzi, S. Srinivasa, and P. Rybski, "Gracefully mitigating breakdowns in robotic services," in *ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 2010, pp. 203–210.
[46] L. Fuentes-Moraleda, P. Díaz-Pérez, A. Orea-Giner, A. Muñoz- Mazón, and T. Villacé-Molinero, "Interaction between hotel service robots and humans: A hotel-specific Service Robot Acceptance Model (sRAM)," *Tour. Manag. Perspect.*, vol. 36, no. 100751, Oct. 2020.
[47] H. Lin, O. H. Chi, and D. Gursoy, "Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services," *J. Hosp. Mark. Manag.*, vol. 29, no. 5, pp. 530–549, 2020.
[48] S. Choi, S. Q. Liu, and A. S. Mattila, "'How may i help you?' Says a robot: Examining language styles in the service encounter," *Int. J. Hosp. Manag.*, vol. 82, pp. 32–38, Sep. 2019.
[49] Y. Lee, S. Lee, and D. Y. Kim, "Exploring hotel guests' perceptions of using robot assistants," *Tour. Manag. Perspect.*, vol. 37, p. 100781, Jan. 2021.
[50] A. Tuomi, I. P. Tussyadiah, and P. Hanna, "Spicing up hospitality service encounters: the case of Pepper™," *Int. J. Contemp. Hosp. Manag.*, 2021.
[51] M. Blut, C. Wang, N. V Wünderlich, and C. Brock, "Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI," *J. Acad. Mark. Sci.*, 2021.
[52] O. H. Chi, S. Jia, Y. Li, and D. Gursoy, "Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery," *Comput. Human Behav.*, vol. 118, p. 106700, 2021.
[53] P. Mongeon and A. Paul-Hus, "The journal coverage of Web of Science and Scopus: a comparative analysis," *Scientometrics*, vol. 106, no. 1, pp. 213–228, 2016.
[54] J. Park, H. Yong, S. Ha, J. Lee, and J. Choi, "Customer-Specific Robotic Attendant for VR Simulators," *IEEE Trans. Autom. Sci. Eng.*, vol. 17, no. 4, pp. 1901–1910, 2020.
[55] A. Parasuraman, V. A. Zeithaml, and L. L. Berry, "SERVQUAL: a Multiple-item Scale for Measuring Consumer Perceptions of Service Quality," *J. Retail.*, vol. 64, no. 1, pp. 12–40, 1988.
[56] A. Parasuraman, V. A. Zeithaml, and L. L. Berry, "Refinement and reassessment of the SERVQUAL instrument," *J. Retail.*, vol. 67, no. 4, pp. 420–450, 1991.
[57] R. Ladhari, "A review of twenty years of SERVQUAL research," *Int. J. Qual. Serv. Sci.*, vol. 1, no. 2, pp. 172–198, 2009.
[58] B. Nemati, H. Gazor, S. N. MirAshrafi, and K. Nazari Ameleh, "Analyzing e-service quality in service-based website by E-SERVQUAL," *Manag. Sci. Lett.*, vol. 2, no. 2, pp. 727–734, 2012.
[59] Y. Zhang and S. Qi, "User Experience Study: The Service Expectation of Hotel Guests to the Utilization of AI-Based Service Robot in Full-Service Hotels," in *International Conference on Human-Computer Interaction*, 2019, pp. 350–366.
[60] F. D. Davis, "Perceived usefulness, ease of use, and user acceptance of information technology," *MIS Q.*, vol. 13, no. 3, pp. 319-340., 1989.
[61] J. van Doorn *et al.*, "Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers' Service Experiences," *J. Serv. Res.*, vol. 20, no. 1, pp. 43–58, 2017.
[62] A. Parasuraman and D. Grewal, "The impact of technology on the quality-value-loyalty chain: A research agenda," *J. Acad. Mark. Sci.*, vol. 28, no. 1, pp. 168–174, 2000.
[63] A. B. Brendel, M. Greve, S. Diederich, J. Bührke, and L. M. Kolbe, "'You are an idiot!' - How conversational agent communication patterns influence frustration and harassment," *26th Am. Conf. Inf. Syst. AMCIS 2020*, pp. 0–10, 2020.
[64] S. Diederich, M. Janßen-Müller, A. B. Brendel, and S. Morana, "Emulating empathetic behavior in online service encounters with sentiment-adaptive responses: Insights from an experiment with a conversational agent," *40th Int. Conf. Inf. Syst. ICIS 2019*, 2020.
[65] R. Ahmad, D. Siemon, and S. Robra-Bissantz, "ExtraBot vs IntroBot: The influence of linguistic cues on communication satisfaction," *26th Am. Conf. Inf. Syst. AMCIS 2020*, pp. 0–10, 2020.
[66] S. Marković, S. Raspor Janković, and V. Zubović, "The impact of robots and artificial intelligence on service quality in the hotel industry," *Balk. J. Emerg. Trends Soc. Sci.*, vol. 3, no. 2, pp. 163–170, 2020.
[67] Z. Tao, Z. Biwen, L. Lee, and D. Kaber, "Service robot anthropomorphism and interface design for emotion in human-robot interaction," *4th IEEE Conf. Autom. Sci. Eng. CASE 2008*, no. September, pp. 674–679, 2008.
[68] C. Bartneck, T. Kanda, O. Mubin, and A. A. Mahmud, "Does the design of a robot influence its animacy and perceived intelligence?," *Int. J. Soc. Robot.*, vol. 1, no. 2, pp. 195–204, 2009.
[69] C. Bartneck, D. Kulić, E. Croft, and S. Zoghbi, "Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots," *International Journal of Social Robotics*, vol. 1, no. 1. pp. 71–81, 2009.
[70] J. W. Jia, N. Chung, and J. Hwang, "Assessing the hotel service robot interaction on tourists' behaviour: the role of anthropomorphism," *Ind. Manag. Data Syst.*, 2021.
[71] D. D. Gremler, "The Critical Incident Technique in Service Research," *J. Serv. Res.*, vol. 7, no. 1, pp. 65–89, 2004.
[72] R. Ladhari, "Developing e-service quality scales: A literature review," *J. Retail. Consum. Serv.*, vol. 17, no. 6, pp. 464–477, 2010.
[73] L. Goodson and J. Phillimore, "A Community Research Methodology: Working with New Migrants to Develop a Policy Related Evidence Base," *Soc. Policy Soc.*, vol. 9, no. 4, pp. 489–501, 2010.
[74] J. (Justin) Li, M. A. Bonn, and B. H. Ye, "Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate," *Tour. Manag.*, vol. 73, pp. 172–181, Aug. 2019.
[75] C. D. Stapleton, "Basic concepts in exploratory factor analysis (EFA) as a tool to evaluate score validity: A right-brained approach," *ERIC Document Reproduction Service No. ED407419*. pp. 1–19, 1997.
[76] G. S. Sureshchandar, C. Rajendran, and R. N. Anantharaman, "Determinants of customer-perceived service quality: A confirmatory factor analysis approach," *J. Serv. Mark.*, vol. 16, no. 1, pp. 9–34, Feb. 2002.