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Recasting service quality for AI-based service

Abstract

Artificial intelligence service agents (AISA), such as chatbots and virtual assistants, are becoming increasingly pervasive in service. Research to date has not adequately addressed how the unique nature of AISA shape consumers' service quality expectations. A deeper understanding of AISA service quality is important for their successful deployment in the service sector. To address this gap, we reviewed marketing and information systems literatures and conducted qualitative in-depth interviews with 37 informants, inclusive of 28 AISA users and nine AISA experts. We developed a conceptual framework for how consumers use and evaluate AISA. Twelve service quality dimensions emerged from the qualitative evidence representing AISA service quality, two of which align with AISA's unique characteristics. The study extends the service quality theory to a new context and offers fresh insights for theory and practice. It culminates with a research agenda to advance research on AISA service quality.

Keywords

Service quality; artificial intelligence; anthropomorphism; proactiveness

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1. Introduction

The service industry is experiencing radical transformation due to artificial intelligence (AI), as evidenced by the growing reliance of companies on AI service agents (AISA) (Davenport et al., 2020; Huang & Rust, 2018). AISA are autonomous technology agents in the form of software applications, machines and robots that can provide customer service by responding to the unique conditions and circumstances of individual consumers (Russell & Norvig, 2016; Wirtz et al., 2018). AISA can engage with consumers in many ways, including addressing queries via chatbots, greeting them at the frontline with social robots and managing health care needs with assistive robots (Huang & Rust, 2018). From a service provider's perspective, the implementation of AISA can facilitate cost-effective service provisioning (Davenport et al., 2020).

A key feature of AISA is the ability to simulate human-like service for consumers facing the AISA (Huang & Rust, 2020; Wirtz et al., 2018). Relative to other forms of technology-based self-service, AISA's learning capability enables them to effectively perform increasingly more complex service tasks (Huang & Rust, 2020). Specifically, there is early evidence that AISA can perform services better than humans and non-AI self-service technology (Wirtz et al., 2018; Xu et al., 2020). On the one hand, AISA can perform certain aspects of service more effectively than service employees since they are not constrained by human limitations of unintended biases and relative inefficiency (Wirtz et al., 2018). On the other hand, relative to non-AI self-service technologies which are generally pedantic in following prescribed interaction rules, AISA can adapt and consequently offer greater scope for customised social engagement with personalisation to consumers in service encounters (Van Doorn et al., 2017; Wirtz et al., 2018). Overall, AISA-based service constitutes a significant shift for service provisioning.

There is consensus that AI will play an increasingly important role in services. Meanwhile, interest in AI in marketing research has grown in recent years (Feng et al., 2020; Mustak et al., 2021). In services marketing, emerging research has predominantly looked at AISA acceptance (Colby et al., 2019; Gursoy et al., 2019; Lu et al., 2019; Paluch et al., 2019; Wirtz et al., 2018; Xu et al., 2020) and continued use (Han & Yang, 2018; Moussawi, 2016). Recent conceptual studies have also examined the scope of the AI impact on services. For example, Wirtz et al. (2018) suggested to investigate the use of service robots at the micro-, meso- and macro-levels. Huang and Rust (2020) examined the effects of different types of AI intelligence on consumer behaviour, services and society at large. Other studies have also proposed frameworks addressing public policy considerations and guidelines to address safety and social desirability concerns associated with AI applications (Dwivedi et al., 2019). While these studies offer a foundation for further research in this rapidly evolving field, there appears to be no research focusing on the important research area of how the use of AISA may influence consumer evaluations of service quality.

To fill this gap, in this study, we develop an AISA service quality framework by examining AISA service quality, including its dimensions, antecedents and outcomes. Based on the definition of service quality (Zeithaml, 1988), we define AISA service quality as the overall excellence or superiority of the service by the AISA as perceived by the consumer. While the service quality construct has undergone significant developments over the last three decades, there is paucity of research concerning if and how well the construct works to explain service quality when service is provided by AISA (Bock et al., 2020; Lu et al., 2020; Ng et al., 2020). This shortcoming is problematic because how consumers assess AISA service quality is influenced by their experiences with AISA and the understanding of this assessment is, by implication, critical for AISA development, adoption and continued use by the consumers. Additionally, since broader trends in the service industry suggest that AISA are likely to replace or play a greater role in facilitating delivery of traditional forms of service, it remains unclear if and how AISA might affect service outcomes (Bock et al., 2020; Lu et al., 2020). Hence, a key research objective that is of interest to researchers, practitioners and consumers is to better understand consumer perceptions related to AISA service quality and if there are any new service quality perceptions which are unique to AISA.

To achieve this objective, we first review and synthesise key literature, including service quality models based on traditional, non-AISA service contexts. The synthesis forms an important foundation which we use as a starting point for identifying key service quality attributes. We subsequently assess these attributes in the context of AISA services. We find that the identified attributes are loaded with meaning which necessitate further qualitative validation. For this purpose, we conducted 37 in-depth interviews to both understand how the identified attributes are perceived by consumers when evaluating AISA service quality and also to potentially identify new attributes representing dimensions arising from the consumers' nuanced experiences with AISA-based services that have not been previously captured. Our analysis and development culminate in a conceptual framework to improve understanding of consumers' perceptions, beliefs and attitudes related to services performed by AISA that is based on a thematic validation of the qualitative evidence.

This study makes the following three key contributions to the literature. First, it extends the service quality knowledge into the AISA context and advances the service quality model. Second, it identifies dimensions of AISA service quality which overall can be used as a diagnostic tool to assess effectiveness of current AI-based services and to inform the design and development of AISA with improved quality and features that are expected by consumers who use them. Third, it develops a research agenda for AISA service quality from the perspectives of consumers, service firms and the broader society.

The remainder of this paper is structured as follows. In the next section, we review related literature on service quality including several service quality scales for varying contexts and analyse their applicability to AISA. We then describe the qualitative research conducted in our study before proceeding with an analysis of our interviews. A conceptual framework is proposed to integrate the insights from the evidence and their interrelationships. We conclude with a discussion of the theoretical and managerial implications from our study and propose a research agenda centred on AISA service quality.

2. Service quality and the impact of AISA

Service quality research offers a significant body of knowledge comprising detailed frameworks and models that have been developed, refined, extended and validated in different service environments (Seth et al., 2005). There is general consensus that service quality is a global assessment and type of attitude[1] that is more enduring than transaction-specific evaluations (Cronin Jr & Taylor, 1994; Parasuraman et al., 1994b). Based on the disconfirmation theory, one perspective of service quality compares service-level expectations against actual performance (Brady & Cronin Jr, 2001; Parasuraman et al., 1985). Accordingly, consumers compare both instrumental (functional) and expressive (psychological) performance outcomes against expectations as a means of assessing service quality (Grönroos, 1984). A more specific measure of expectations considers a tolerance zone between desired *versus* minimum expectation levels in which service performance is deemed to be satisfactory (Parasuraman et al., 1993; Parasuraman et al., 1994a).

The subjectivity of service assessments (Zeithaml et al., 1985) led scholars of early studies to improve understanding of service quality for face-to-face service contexts.

[1] The literature recognises service quality as a long-term global judgement at an attitude level (Cronin Jr & Taylor, 1994; Parasuraman et al., 1994b). This attitude can be formed by the sum of transaction-specific customer satisfaction evaluations (Parasuraman et al., 1994b).

Accordingly, the majority of human service quality research occurred in the 1990s, with technology-enabled service quality research taking place in the 2000s. With advances in service innovation using technology (Huang & Rust, 2018), insights from the information systems (IS) literature were integrated with the services management literature to develop scales that address self-service technologies and applications that run on distributed infrastructures, such as the internet (e.g. Ding et al., 2011; Loiacono et al., 2007; Yang et al., 2004).

Research involving service quality remains relevant in the literature. The seminal SERVQUAL scale by Parasuraman et al. (1988) continues to be featured in studies involving consumer evaluations of human service environments (e.g. Hussain et al., 2019; Rosenbaum & Russell-Bennett, 2020) as well as those investigating technology-based service environments (e.g. Xiao & Kumar, 2019). Recent empirical studies have also adapted SERVQUAL in the context of AISA (Morita *et al.*, 2019, Meyer-Waarden *et al.*, 2020).

Consumer evaluations of service quality can change based on the uniqueness of the service agent, the nature of service delivery and the overall service environment (Rust & Oliver, 1993). Accordingly, Parasuraman et al. (2005) asserted that an adaptation of SERVQUAL (Parasuraman et al., 1988) for the online service environment was not appropriate. Thus, new dimensions not captured in SERVQUAL, but relevant for website-based services (e.g. 'system availability'), were introduced in the new E-S-QUAL scale. The service quality models and respective dimensions developed for various service environments are summarised in Table 1[2].

[Insert Table 1 here]

[2] Based on a review of seminal service quality scales and key studies from 1988 to 2020, with consumers as end users. Scales were selected based on their significance in tapping into the different service environments relevant to AISA.

Table 1 highlights the potential of AI as the next wave of technology advancement in service innovation. As can be seen from our synthesis in Table 1, AISA can perform in a wide variety of human and technology service environments (see e.g. last column of Table 1). For instance, the technology-based self-service nature of AISA is captured by Dabholkar (1996), Ding et al. (2011) and Lin and Hsieh (2011), with its ancillary role highlighted by TeleServQ (He et al., 2017). The ability of AISA to provide human-like personalised service can also be inferred through service quality scales involving human service agents, such as Mittal and Lassar (1996). In addition, the need for AISA to respond dynamically to various voice service requests parallels that of call centres (Burgers et al., 2000).

However, none of the service quality measures are readily applicable to AISA. Empirical evidence from recent service quality studies investigating different types of AISA have also concluded that SERVQUAL was unable to adequately capture the service performance of robots in cafes (Morita et al., 2019) and chatbots (Meyer-Waarden et al., 2020). Indeed, the uniqueness of AISA has changed the nature of service delivery, the overall service environment, with implications for consumer evaluations of AISA service quality (Rust & Oliver, 1993). Using a variety of techniques, such as speech recognition, natural language processing and machine learning[3] to achieve intelligence (Jordan & Mitchell, 2015), AISA can perform autonomously in diverse service environments (Legg & Hutter, 2007). Indeed, AISA feature significant improvements in performing well-defined, automated tasks (Davenport et al., 2020), and are already showing the potential to become capable of performing more intuitive and empathetic tasks in the future (Huang & Rust, 2018).

Another key distinctive characteristic of AISA is the degree of anthropomorphism (Bartneck et al., 2009; Goudey & Bonnin, 2016; Moussawi, 2016). A consumer interacting

[3] Machine learning is an algorithm-based process which enables the AI application to automatically improve its task performance by learning from data patterns and experience as opposed to pre-programmed responses (Jordan & Mitchell, 2015).

with an anthropomorphic AISA, whether in abstract psychological form, such as virtual assistants and chatbots or in more physical forms such as humanoid robots, can develop perceptions of social presence (Qiu & Benbasat, 2009; Van Doorn et al., 2017) which increase trust and enjoyment from service interactions with AISA (Qiu & Benbasat, 2009; Troshani et al., 2020).

It is clear that AISA can provide human-like service which in turn creates customer experiences that are likely to be somewhere between the experiences derived from human-based services and experiences derived from the interaction with technology-based service systems. What is less clear is which service quality dimensions that have been traditionally used to assess human- or technology-based service experiences are important for consumers in their evaluation of AISA and the extent to which such dimensions are important (Bock et al., 2020; Lu et al., 2020). Additionally, given the unique features of AISA (e.g. intelligence and anthropomorphism) and the new capability that is associated with these features, it is reasonable to expect the possibility that there might be new service quality attributes that operate within the AISA service environment that were not present in traditional service environments (Bock et al., 2020).

3. Method

To investigate how consumers use and evaluate AISA, we adopted an exploratory qualitative approach by using semi-structured in-depth interviews. We used this approach to gain a deeper understanding of the perceptions and concerns that individuals have about AISA. Interviewees were comprised of active AISA users and experts, including researchers and specialists. As recommended by Malhotra et al. (2017), in addition to the user-group, expert views from researchers and specialists can be useful in understanding perspectives relevant to

AISA service quality. All interviews were conducted by the lead author following a standard interview protocol for all interviewees.

The interview protocol was developed based on extant literature and the research questions and was subjected to multiple iterations of refinements by the co-authors. The protocol guided discussion pertaining to (1) consumers' perceptions of key service quality attributes involving AISA, (2) concerns associated with AISA's provisioning of quality service, (3) how services performed by AISA affect consumers. Protocol wording was adapted to suit interviewee roles. Overall, protocol questions were designed with the common objective of uncovering the key attributes that mattered to consumers when evaluating AISA service quality.

3.1 Choice of AISA

Chatbots and virtual assistants were deliberately used as representative AISA types in the interviews. Chatbots are used by individuals via company websites, messaging applications and standalone apps to facilitate product/service-related queries and processes specific to a business. In response to the user's text-based messages, chatbots can typically provide service solutions using text, images and supporting links (Zarouali et al., 2018). Virtual assistant applications are predominantly voice-based and widely available in smartphones and internet-connected devices (Hoy, 2018). In addition, virtual assistants can connect with other third-party applications and allow users to perform routine tasks such as reading emails, sending text messages or facilitating phone calls for the users (Siddike et al., 2018).

Overall, chatbots and virtual assistants are becoming increasingly popular (Research, 2020), and the scope of tasks they can perform is growing rapidly. We deliberately focused on both chatbots, used in different industries, and virtual assistants since the differences between these applications as used by consumers can provide additional context for testing the robustness of a service quality scale for AISA (Parasuraman et al., 1985; Parasuraman et al., 2005; Zeithaml et al., 2000). Additionally, these types of AISA have been available for some time and are widely accessible to consumers. The goal was that, with the right informants, we could tap into extensive experience that would enable us to collect meaningful qualitative evidence for the purpose of this study.

3.2 Interviewees

Interviewees were purposely selected as individuals who had used chatbots and/or virtual assistants during the three months prior to the interview. A total of 28 users, split evenly by gender and each AISA type (chatbots/virtual assistants), were interviewed between May and July 2019. The interviewees' ages ranged between 24 and 52 years of age. Half of the interviewees who identified themselves as predominantly chatbot users had used chatbots in website and messenger platforms related to accessories, beauty, food, finance, government, hospitality, mobile and IT services. The remaining 14 interviewees identified themselves primarily as users of virtual assistants.

In addition to the 28 user interviewees, nine AISA experts consisting of researchers and specialists were also interviewed. Their ages ranged between 25 and 35, and they comprised academic researchers in Applied AI, AI consultants, AI data scientists and a machine learning engineer. These AISA experts could give deeper insights into AISA which apply across both chatbots and virtual assistants. Their views were triangulated against the user interviewees to provide a better understanding of the technical and organisational considerations surrounding AISA service quality. Table 2 summarises the profiles of all interviewees. To maintain promised confidentiality and conditions of ethics approval, specific details about the interviewees are not disclosed in the paper.

[Insert Table 2 here]

3.3 Data collection and analysis

All interviewees were recruited via snowball sampling through mainly colleagues and professional networks. These interviewees resided in Australia and Singapore – both countries scoring high in terms of their current AISA adoption (Kinsella, 2019; Yang, 2018) and readiness for future AISA services (Insights, 2019). Where traditional face-to-face interviews were not feasible (e.g. due to distance), online interviews (e.g. via Skype) were used instead. The same interview protocol was used for all interviewees in both Australia and Singapore. Interviewees were given a $20 gift voucher, based on their respective home currencies, as a symbolic reward for their participation. Interviewees were also informed of a formal ethics approval secured for the study from the university with which the co-authors are affiliated. All interviews were digitally recorded and transcribed. Interviewees were also given a copy of their own transcripts to verify the responses given. Transcripts were then formatted and analysed by the co-authors.

Transcripts were subjected to a thematic analysis in an incremental fashion using the 'Gioia methodology' (Gioia et al., 2013). This qualitative analysis methodology shows how the informants' perspectives (first order concepts) are taken into account by the researchers before being organised and transformed into theory-centric themes (second order themes) and aggregated dimensions (Gioia et al., 2013). Accordingly, transcripts were subjected to two rounds of coding using NVivo (version 12), a widely-used computer-assisted qualitative analysis tool (Sotiriadou et al., 2014). The first round consisted of coding words and phrases in the transcript while the second round involved grouping the codes (captured as nodes) into themes and dimensions (Gioia et al., 2013; Sotiriadou et al., 2014). To increase the accuracy of our findings, dimensions were triangulated against service quality dimensions in the extant literature (i.e. data triangulation) and also among the different researchers in this study (i.e. investigator triangulation) (Patton, 2002). As for reliability, the use of NVivo assisted in establishing a chain of evidence (Yin, 2009), as it was possible to efficiently trace our research findings and codes back to the source data interviews (Bonello & Meehan, 2019). Through a process of axial coding (Strauss & Corbin, 1998), several salient perceptions of AISA service quality emerged. Table 3 illustrates the frequency of the final codes captured in NVivo.

[Insert Table 3 here]

In the following section, we first define the domain of AISA service quality before discussing a range of influencing factors including dimensions, antecedents, and outcomes based on our findings. We then develop a framework integrating these components before discussing implications.

4. Analysis and findings

The findings of this study recognise AISA service quality as the extent to which AISA facilitate an overall perception of excellence or superiority by consumers. Based on extant research, we also conceptualise AISA service quality as a global assessment and a long-term attitude (rather than a short-term judgement) towards a specific service encounter with AISA.

AISA service quality consists of dimensions based on the perceptual attributes of services performed by AISA as mapped in the means-end framework (Parasuraman et al., 2005). Developing the dimensions of AISA service quality based on the perceptual level effectively captures the abstract nature of service-quality comparisons which consumers make across categories (Zeithaml, 1988). Evaluations at the attribute level also lead to a more global assessment of service quality (as opposed to transaction-specific assessments) (Parasuraman et al., 2005). Accordingly, AISA service quality is a form of attitude (Parasuraman et al., 1988).

We posit that AISA service quality is shaped by consumer perceptions of AISA, AISA characteristics, service features and attitudes towards AISA. Service performance perceptions of AISA can be formed by consumers who have been regular recent users of AISA. These perceptions are influenced by the design and technical aspects of AISA which form its antecedents. These performance perceptions can also produce various consumer outcomes. In addition, the relationships between AISA service quality and its outcomes are also affected by situational and consumer-related factors.

These components and their interrelationships – which describe how consumers use and evaluate AISA-based services as well as the attributes which matter to them – are discussed in detail in the following sections.

4.1 Antecedents of AISA service quality

The antecedents are factors that can influence the dimensions of AISA service quality. These include its design and technical aspects (cf. Parasuraman et al., 2005). For instance, AISA design can be comprised of size and shape attributes in the physical (e.g. smart speakers) or virtual form (e.g. appearance of chatbot window). Antecedents can also include more functional design aspects such input, interface and output methods (Kepuska & Bohouta, 2018) or technical aspects such as hardware and software capabilities that affect both chatbots and virtual assistants. As noted by AIDS 1: *"As quantum computing matures, I think that we might see something that can help ingest those vast amounts of information"*.

While advances in technology such as natural language processing continues to improve AISA performance (MSV, 2019), it is also important that current applications including chatbots and virtual assistants be trained correctly to avoid biases which can affect service performance. As commented by AIC 2: *"About the bus service… so, this particular model is trained in the white district area... But then, it will leave out the black kids behind and even forget to pick up those kids"*.

Unlike the dimensions of AISA service quality which are based on the perceptual attributes that constitute the components of service quality measurement, the above antecedents are causal factors which may differ across various AISA or change in time. For instance, while chatbots and virtual assistants often rely on different input methods (i.e. text or voice respectively), future dialogue systems may become more interactive and integrate other forms such as gestures and user movements (Kepuska & Bohouta, 2018).

4.2 Perceptions of AISA service quality

From the literature review as well as qualitative interviews with AISA users and expert informants, 12 aggregated dimensions of AISA service quality have emerged as shown in the data structure (Gioia et al., 2013) built in Table 4. We now define each dimension and discuss them in relation to the service quality literature. We provide supporting evidence by using illustrating quotes for each dimension in Table 4.

[Insert Table 4 here]

Reliability refers to the ability of the AISA to perform the service dependably and accurately (Parasuraman et al., 1988). Three themes emerged as important when assessing the reliability of AISA: command recognition, intent recognition and task fulfilment; and correspond with the sequential order in which AISA process commands that are given to them (Ng, 2019). Consumers expect the AISA to support them in accomplishing their activities with little informational or functional lapses (Tan et al., 2016). The reliability dimension also appears frequently in extant service quality literature involving both human (e.g. Parasuraman et al., 1988) and technology-based service scales (e.g. Dabholkar, 1996). Not surprisingly, the interviewees emphasised reliability to be one of the key dimensions they use to assess the service performance of AISA.

Responsiveness refers to the prompt response of the AISA to consumer requests and the speed in resolving consumer problems (Yang et al., 2004). Like reliability, responsiveness was found to be a prevalent service quality attribute that users seek in both human- (e.g. Brady & Cronin Jr, 2001) and technology-based service contexts (e.g. Loiacono et al., 2007). For AISA users, responsiveness also includes minimising the waiting time needed to activate the AISA to perform the service task (cf. Dabholkar, 1996). Such delays in access constitute a system failure that can lead to frustration (Tan et al., 2016).

Availability refers to the ability of AISA to be ready for use anytime, anywhere (Lin & Hsieh, 2011; Parasuraman et al., 2005). As with human- (e.g. Dabholkar et al., 1996) and technology-based service environments (e.g. Yang et al., 2005), this is a fundamental systems requirement (Tan et al., 2016) that is appreciated by consumers. However, unlike virtual assistant users who can easily access their AISA via mobile phones, the accessibility of AISA was stressed by chatbot users who wanted more industries to adopt such AISA in their websites.

Aesthetics refers to the appeal and clarity associated with the AISA interface design (Dabholkar et al., 1996). The aesthetic consideration extends beyond visual assessments commonly used in other human- (e.g. Brady & Cronin Jr, 2001) and technology-based service quality scales (e.g. Loiacono et al., 2007) to include other properties relevant for AISA such as speech and audio (Kepuska & Bohouta, 2018). This aesthetical assessment can also be affected by the surrounding interface design in which the AISA operates.

Personalisation refers to the ability of the AISA to meet the consumers' individual preferences (He et al., 2017). This can come in the form of adapting to the context of the task or providing warm attention (Burgers et al., 2000). To compensate for the reduction in human empathy once offered by human service agents in the service environment (e.g. Mittal & Lassar, 1996), technology-based service systems focused on delivering service information that can be customised (e.g. He et al., 2017) and tailored (e.g. Loiacono et al., 2007) to fit user requirements. Advances in technology including the availability of big data have also helped to enhance service personalisation (Rust & Huang, 2014). With AISA, a spectrum of personalisation capabilities can now be better realised from technology-based systems as AISA can learn and adapt to user behaviour based on available data (Thomaz et al., 2020). Continued technological innovation will increase this level of customisation (Pantano & Pizzi, 2020) and improve AISA's system performance (Tan et al., 2016).

Security refers to the perceived safety of the AISA from intrusion, fraud and loss of personal information and privacy (He et al., 2017). Sensitivity about relinquishing one's personal data and its security began to gain prominence as an important dimension as service environments moved from human to technological contexts (e.g. Parasuraman et al., 2005). On the one hand, these privacy concerns will continue to become more prevalent in the IS domain with emerging AISA technologies (Conger et al., 2013; Dwivedi et al., 2019) and the need to make AISA's decision making processes more transparent (Rai, 2020). On the other hand, AISA such as chatbots can also facilitate service provisioning for users with varying privacy concerns (Thomaz et al., 2020). Although interviewees understood that personal information is required by the AISA to personalise its performance for the user, they still desired a level of control and protection with regards to their privacy and personal information.

Control refers to the degree of control that consumers feel they have over the process or outcome of the service encounter with AISA (Dabholkar, 1996). This dimension is prevalent for new system implementation (Baronas & Louis, 1988) and became more important as consumers began using more technologies to perform the services for themselves (Ding et al., 2011). In line with AISA being self-service platforms, our interviewees expressed the importance of their desire to have some control over AISA and reduce the AISA influences.

Ease of use refers to the degree to which using AISA would be free of effort (Davis, 1989). This dimension became relevant in the service quality literature with the introduction of self-service technologies in contexts such as touch screens in fast food restaurants (Dabholkar, 1996) and website services (Yang et al., 2004). Treating AISA as an extension of a form of self-service technology, interviewees expected the use of AISA to be easy and provide a seamless integration into their everyday lifestyle.

Enjoyment refers to the extent to which using the AISA is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated (Davis et al., 1992). In this regard, the use of AISA extends beyond pure utilitarian performance to include hedonic perceptions of enjoyment. Such an entertainment value was also assessed by consumers for past technology-based service environments (e.g. Dabholkar, 1996; Lin & Hsieh, 2011; Loiacono et al., 2007). Similarly, the enjoyment can come from the interaction with AISA or from the novelty of being associated with service innovations such as AISA (Dabholkar, 1996).

Contact refers to access to human assistance (Parasuraman et al., 2005). Like several technology-based self-service environments such as the internet (e.g. Parasuraman et al., 2005), mobile (e.g. Huang et al., 2015) and telematics (e.g. He et al., 2017), users expect AISA to provide the option for human support. In this regard, the user may decide to initiate contact during or after service interaction. The organisation too can increase its level of service by following up with the consumer when required.

Proactiveness refers to AISA displaying self-started, long-term-oriented, and persistent service behaviour beyond explicitly prescribed commands (Rank et al., 2007). Beyond just reacting to every user command, the ability of AISA to be proactive can be important when users may have overlooked tasks which need to be done or which they are unaware of due to the unfamiliar service context. This dimension can include assisting consumers with alternatives (Tan et al., 2016). Proactiveness represents a new service quality dimension.

Anthropomorphism refers to the attachment of human-like characteristics, motivations, intentions, or emotions to AISA (Epley et al., 2007). Anthropomorphism could come in an abstract form via an experience the user has with AISA or by way of other distinct cues. These anthropomorphistic design cues can assist in reducing privacy concerns about AISA (Benlian et al., 2019). However, consumers may also experience a negative side-effect, termed ‘counterfeit service’, which is when they realise that the service was performed by AISA and not humans (Robinson et al., 2019). Anthropomorphism represents another new service quality dimension in the literature.

4.3 Consumer outcomes

After the formation of service quality perceptions, several outcomes such as consumer satisfaction, perceived value and continued use of AISA were indicated (Cronin Jr et al., 2000). As VAUS 1 noted: *“So, I think what would make me satisfied is when the virtual assistant reaches a point where it's no longer intrusive… but it becomes an ally”.*

In terms of behavioural outcomes, informants also indicated that the frequent use of AISA can lead to good habits due to the devices’ ability to monitor user behaviour patterns and send reminders. As VAUA 1 commented: *“But when it's a manual habit you're trying to inculcate, it's more challenging compared to when you have a tool, a device that will do it on your behalf... so it's good habits being inculcated”.*

Such a dependency also caused informants to worry that they were becoming lazy. However, many indicated that they did appreciate the productivity aspects that AISA brought to their lives (cf. Parasuraman, 2002). CUF 4 stated: *“Because just by inputting details, they can somehow create a report for us. Where if I were to do it on my own, it will take a bit of time for me to consolidate all the info”.*

Beyond the behavioural outcomes of service quality (Zeithaml et al., 1996), consumers also experienced cognitive and affective impacts that AISA might have on them. In terms of the link between the brand image of AISA and the company it represented, it was unclear how informants would associate the brand attributes of the company with the AISA (cf. Wu et al., 2011). As CUF 2 noted: *"XYZ Bank is a secured banking site… I've never had issues with banking online and things like that. But I don't have a lot of experience with chatbots and I don't want to be one of the unlucky ones for example if there's an issue with the chatbot"*.

Interviewees also indicated that the use of AISA can affect psychological well-being in several ways (cf. Mogaji et al., 2020) and subjective well-being (Diener, 1984). For instance, although AISA can help facilitate personal growth, they may also cause a dependency on the technology and affect the quality of relationships with others. VAUGA 5 commented *"If you talk about emotional – look at the sheer number of instances in Japan where the guy's married a pillow, married a digital entity, married a game and they have companionship… in my mind, that's just scary"*.

4.4 Role of situational and consumer-related factors

The direction and/or strength of the relationship between AISA service quality and its outcomes can be affected by a range of factors in relation to the situation and the AISA consumer. In terms of situational factors, first, informants indicated that time pressures and the perceived urgency of the service may affect their future decisions about the use of AISA, including chatbots and virtual assistants (Dabholkar & Bagozzi, 2002). As stated by AIDS 4: *"But if it's urgent, I need to file my tax returns in 10 minutes before the deadline is over, I'm not going to go through a chatbot. I want to go straight to the person"*.

Informants also indicated a level of uncertainty about the use of AISA to perform services traditionally performed by humans. This perceived risk (Dowling & Staelin, 1994) can result in consumers becoming more uncertain of future service performances (Aldas-Manzano et al., 2011) which may constrain future use. VAUS 4 commented: *"I think that could lead to some detrimental results; Siri could have possibly booked a flight which I don't desire"*.

While AISA can lead to new habits being formed, previous consumer habits and social norms can also play a role in shaping future usage of AISA service quality. As noted by VAUS 1: *"... it's not socially normal to be talking to your phone"*.

In terms of consumer-related factors, the level of technology readiness of informants to accept and utilise AISA – consisting of motivating (optimism and innovativeness) and inhibiting (discomfort and insecurity) factors (Parasuraman, 2000; Parasuraman & Colby, 2015) – was also found to be significant in the AISA context. CUBF 1 commented: *"I like the whole technological advancements. I really like engaging with new technology, and just testing the limits… Because I think technology will get us somewhere, but if people keep rejecting it, it would just take so much longer"*.

Finally, informants also indicated that they will avoid AISA for specific services where the interaction with a human being is deemed critical for a successful service performance (Dabholkar & Bagozzi, 2002). As VAUS 1 noted: *"If you're talking about people who are going to enrich lives, who are going to be with him for four years, or six years, or ten years – I think there still needs to be a person with complex emotions, complex thinking, with years of experience"*.

5. Discussion

Our qualitative interviews provided rich insights into the dimensions that consumers use in evaluating AISA service quality and a range of factors including antecedents and outcomes surrounding AISA service quality including situational and consumer-related factors that influence the identified relationships. We developed a conceptual framework based on our findings which we present in Figure 1. The framework synthesises the relationships between the identified factors.

[Insert Figure 1 here]

Figure 1 shows a unique combination of dimensions from extant human and technology-based service quality scales which are relevant to the AISA service quality environment: reliability, responsiveness, availability, aesthetics, personalisation, security, control, ease of use, enjoyment and contact. These dimensions demonstrate the ability of AISA to tap into a wide spectrum of human and technology service quality dimensions and support the notion of AISA as a significant, promising new wave of technology-driven advancement in service innovation. Of these, human contact continues to remain important, even for an advanced self-service technology, such as AISA, in increasing customer satisfaction among AISA consumers (Barrett et al., 2015; Shell & Buell, 2019). However, the future relevance of human contact in service quality is questionable as AISA continues to provide more advanced human-like service (Huang & Rust, 2018; Huang & Rust, 2020).

In addition, two new dimensions in service quality were identified which are unique to AISA services. The first dimension, proactiveness, is closely related to the intelligence trait of AISA and its predictive ability to anticipate future needs. Compared to human service agents, proactiveness is also more likely to be realised in the AISA service environment as there is no risk of additional effort or cost being required on the part of AISA to be proactive (Wirtz et al., 2018). However, with a greater exercise of initiative from AISA also comes the question of perceived control, and the extent to which the consumers might feel comfortable with AISA having a greater control in the service environment.

Anthropomorphism represents another new dimension that our study contributes to the service quality literature. Specifically, our study shows how consumers may use different forms of anthropomorphic cues to assess AISA service quality (cf. Go & Sundar, 2019). As it is reasonable to surmise that continued AI innovation will result in future AISA having more anthropomorphic potential, greater clarity is required to better understand how consumers anthropomorphise AISA (Novak & Hoffman, 2019), and the contexts to which anthropomorphism leads to user discomfort (i.e. the 'uncanny valley') (Bakpayev et al., 2020; Davenport et al., 2020; Lu et al., 2019; Mori et al., 2012; Troshani et al., 2020).

With reference to Figure 1, many service quality studies have looked at satisfaction, perceived value and continued use outcomes to test the predictive validity of their constructed scales (e.g. Ding et al., 2011; Loiacono et al., 2007; Parasuraman et al., 2005; Yang et al., 2004). Our framework supports the use of these outcomes for the nomological validation of a future empirical scale developed for AISA service quality. Such a validation of the relationship between AISA service quality and the variable of continued use can be particularly important to show how AISA service quality can promote the growth and sustainability of AISA in service (Seth et al., 2005).

Of the various situational and consumer-related factors that influence the relationships AISA service quality and outcomes identified in Figure 1, the level of technology readiness of consumers was found to affect their decision to use AISA in the long run. This supports the proposition of Zeithaml et al. (2002) who posited the role of technology readiness in affecting website service quality. As for perceived risk, informants did not express perceived risk as a switching barrier (Tam, 2012) but rather as having an inverse effect on loyalty due to unstable satisfaction levels with current AISA (Tuu et al., 2011). Overall, these insights support the recent call by scholars to better understand consumers' resistance to digital innovations including AISA (Talwar et al., 2020).

6. Conclusion

6.1 Theoretical implications

Despite a rich tradition of assessing service quality in various service environments, current service quality research has yet to investigate the fast-emerging AISA service that consumers are experiencing, and their perceptions and expectations when services are performed by AISA. Our research takes a first step to go beyond conceptualising AI-based services, which has been the subject of emerging research in the use of AI in service (Bock et al., 2020; Huang & Rust, 2020; Wirtz et al., 2018). We investigate the current state of consumer experiences with AISA to advance the service quality model. Through an interdisciplinary review of the services marketing and IS literatures and in-depth interviews with AISA users and experts, our framework provides a nuanced understanding of the key antecedents, dimensions and outcomes of AISA service quality as perceived by consumers.

A key objective of our study was to answer the question of how well traditional service quality dimensions apply to the AISA context and if there are any new unidentified dimensions that were relevant for AISA (Bock et al., 2020; Lu et al., 2020; Ng et al., 2020). With reference to Table 1, 10 of the 12 AISA service quality dimensions identified suggest a confirmation of past service quality dimensions found in extant service quality measurements. Further scrutiny of these 10 dimensions in relation to extant human service quality scales suggests that consumers evaluate AISA service quality, in part, along six service quality dimensions salient to human service agents: reliability, responsiveness, availability, aesthetics, personalisation and security. This highlights the potential of AISA to substitute human service quality performances within these six dimensions.

By contrast, all 10 service quality dimensions are captured in extant technology-based service quality scales (see Table 1). While this may suggest that consumers evaluate AISA service quality in a similar fashion to other non-AI based technologies, the uniqueness of AISA service quality is evidenced by two factors: first, the presence of two new service quality dimensions found in our study – proactiveness and anthropomorphism – and second, the unique combination of the 12 dimensions which is representative of the gestalt of consumer perceptions of AISA service quality.

Upon further inspection, when we compared the AISA service quality dimensions (except proactiveness and anthropomorphism) to the 11 dimensions of electronic service quality as identified by Zeithaml et al. (2000) (which were subsequently reduced to four dimensions during the empirical development of E-S-QUAL), almost all dimensions were similar to one another. The exceptions were enjoyment (from AISA service quality) and price knowledge (from electronic service quality). This suggests that AISA consumers place importance on the hedonic attribute of enjoyment of AISA when evaluating AISA service quality.

It is also worth highlighting the theoretical significance of the anthropomorphism dimension in our study. In addition to its novel introduction as a perceived attribute of service quality, our findings provide support for the emerging theme in the literature that emphasise the important role of anthropomorphism in AISA service (e.g. Benlian et al., 2019; Sheehan et al., 2020; Troshani et al., 2020). In addition, our study provides a new basis for leveraging the impetus for exploring this new dimension in AISA service quality.

Overall, these findings extend the theory of service quality and contributes to the foundation for the development of an empirical AISA service quality scale which can be used to ascertain the generalisability of our 12 dimensions across different AISA types and industries as used by consumers, and to streamline the dimensions accordingly (cf. Parasuraman et al., 2005).

6.2 Managerial and social implications

Our findings provide managerial and social insights that can inform the strategies of service providers, business leaders and policy makers. First, in addressing proactiveness as a new service quality dimension, it is important to ensure that the development of AISA includes specifications for the AISA to be able to interact with multiple applications (e.g. facilitated via the Internet of Things (IoT)) (Huang & Rust, 2018) to enhance the AISA's proactive range in recommending a variety of solutions for users. Users should also be aware of the ability to control AISA settings and choose the level of personalisation vis-à-vis privacy trade-offs with which they are comfortable.

Second, as anthropomorphism is important and unique to AISA service, consumer involvement needs to be facilitated in the development and design process of AISA (Bitner et al., 2000; Steinhoff & Palmatier, 2020) to understand public sentiment and test the effectiveness of new anthropomorphic attributes in improving AISA service experience (Benlian et al., 2019; Steinhoff & Palmatier, 2020). It should also be made clear to consumers if and when they are interacting with AISA as some may be misled into thinking that their interaction was with a human service agent rather than AISA (Robinson et al., 2019). This might be a critical uptake consideration given the possible implications of the phenomenon of the 'uncanny valley'.

Our study also highlights the importance of careful implementation of AISA, particularly in services traditionally performed exclusively by human service agents. In the early phases of piloting AISA, human service support should continue to be readily available to consumers. In this service environment, AISA should be used to complement human service agents to provide an overall positive service experience for consumers.

Overall, while service professionals can continue to manage human-to-human service provisioning using measurements such as SERVQUAL, and website services with E-S-QUAL, with AISA they now have a means to improve AISA service quality using the proposed 12 dimensions. Development and continuous improvement of AISA can also be facilitated through consumer feedback of the overall AISA service quality or based on specific dimensions.

6.3 Future research: a research agenda for AISA service quality

The field of AI-based services is developing fast. There are research opportunities arising from our findings, in terms of its impact on AISA users, AISA service providers and society at large. Drawing on the range of issues discussed, the proposed research agenda shown in Table 5 identifies important research questions which would extend our understanding of the opportunities and challenges involved in AISA service quality.

[Insert Table 5 here]

References

Aldas-Manzano, J., Ruiz-Mafe, C., Sanz-Blas, S., & Lassala-Navarré, C. (2011). Internet banking loyalty: evaluating the role of trust, satisfaction, perceived risk and frequency of use. *The Service Industries Journal, 31*(7), 1165-1190.

Bakpayev, M., Baek, T. H., van Esch, P., & Yoon, S. (2020). Programmatic creative: AI can think but it cannot feel. *Australasian Marketing Journal (AMJ)*.

Baronas, A.-M. K., & Louis, M. R. (1988). Restoring a sense of control during implementation: how user involvement leads to system acceptance. *MIS Quarterly*, 111-124.

Barrett, M., Davidson, E., Prabhu, J., & Vargo, S. L. (2015). Service innovation in the digital age: key contributions and future directions. *MIS Quarterly, 39*(1), 135-154.

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics, 1*(1), 71-81.

Benlian, A., Klumpe, J., & Hinz, O. (2019). Mitigating the intrusive effects of smart home assistants by using anthropomorphic design features: A multimethod investigation. *Information Systems Journal*, 1-33. doi:10.1111/isj.12243

Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology infusion in service encounters. *Journal of the Academy of Marketing Science, 28*(1), 138-149.

Bock, D. E., Wolter, J. S., & Ferrell, O. (2020). Artificial intelligence: disrupting what we know about services. *Journal of Services Marketing*.

Bonello, M., & Meehan, B. (2019). Transparency and coherence in a doctoral study case analysis: Reflecting on the use of NVivo within a 'Framework' approach. *The qualitative report, 24*(3), 483-498.

Brady, M. K., & Cronin Jr, J. J. (2001). Some new thoughts on conceptualizing perceived service quality: a hierarchical approach. *Journal of Marketing, 65*(3), 34-49.

Burgers, A., de Ruyter, K., Keen, C., & Streukens, S. (2000). Customer expectation dimensions of voice-to-voice service encounters: a scale-development study. *International Journal of Service Industry Management, 11*(2), 142-161.

Colby, C., Mithas, S., & Parasuraman, A. (2019). *Service robots: Trends in acceptance and factors behind readiness to adopt*. Paper presented at the Frontiers in Service 2019, Singapore.

Conger, S., Pratt, J. H., & Loch, K. D. (2013). Personal information privacy and emerging technologies. *Information Systems Journal, 23*(5), 401-417.

Cronin Jr, J. J., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of Retailing, 76*(2), 193-218.

Cronin Jr, J. J., & Taylor, S. A. (1994). SERVPERF versus SERVQUAL: reconciling performance-based and perceptions-minus-expectations measurement of service quality. *Journal of Marketing*, 125-131.

Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: an investigation of alternative models of service quality. *International Journal of Research in Marketing, 13*(1), 29-51.

Dabholkar, P. A., & Bagozzi, R. P. (2002). An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. *Journal of the Academy of Marketing Science, 30*(3), 184-201.

Dabholkar, P. A., Thorpe, D. I., & Rentz, J. O. (1996). A measure of service quality for retail stores: scale development and validation. *Journal of the Academy of Marketing Science, 24*(1), 3-16.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24-42.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology, 22*(14), 1111-1132.

Diener, E. (1984). Subjective well-being. *Psychological Bulletin, 95*(3), 542-575. doi:10.1037/0033-2909.95.3.542

Ding, D. X., Hu, P. J.-H., & Sheng, O. R. L. (2011). e-SELFQUAL: A scale for measuring online self-service quality. *Journal of Business Research, 64*(5), 508-515.

Dowling, G. R., & Staelin, R. (1994). A model of perceived risk and intended risk-handling activity. *Journal of Consumer Research, 21*(1), 119-134.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., . . . Eirug, A. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 101994.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: a three-factor theory of anthropomorphism. *Psychological review, 114*(4), 864.

Feng, C. M., Park, A., Pitt, L., Kietzmann, J., & Northey, G. (2020). Artificial intelligence in marketing: A bibliographic perspective. *Australasian Marketing Journal (AMJ)*.

Gioia, D. A., Corley, K. G., & Hamilton, A. L. (2013). Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods, 16*(1), 15-31.

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior, 97*, 304-316.

Goudey, A., & Bonnin, G. (2016). Must smart objects look human? Study of the impact of anthropomorphism on the acceptance of companion robots. *Recherche et Applications en Marketing (English Edition) (Sage Publications Inc.), 31*(2), 2-20. doi:10.1177/2051570716643961

Grönroos, C. (1984). A service quality model and its marketing implications. *European Journal of Marketing, 18*(4), 36-44.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157-169.

Han, S., & Yang, H. (2018). Understanding adoption of intelligent personal assistants: A parasocial relationship perspective. *Industrial Management & Data Systems, 118*(3), 618-636. doi:doi:10.1108/IMDS-05-2017-0214

He, Z., Yang, X., Wang, W., & Zhang, M. (2017). Measuring service quality in telematics service: development and validation of multidimensional TeleServQ scale. *Total Quality Management & Business Excellence, 28*(9-10), 1166-1182.

Hoy, M. B. (2018). Alexa, Siri, Cortana, and More: An introduction to Voice Assistants. *Medical Reference Services Quarterly, 37*(1), 81-88.

Huang, E. Y., Lin, S.-W., & Fan, Y.-C. (2015). M-S-QUAL: Mobile service quality measurement. *Electronic Commerce Research and Applications, 14*(2), 126-142.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155-172.

Huang, M.-H., & Rust, R. T. (2020). Engaged to a Robot? The Role of AI in Service. *Journal of Service Research*, 1094670520902266.
Hussain, K., Jing, F., Junaid, M., Bukhari, F. A. S., & Shi, H. (2019). The dynamic outcomes of service quality: a longitudinal investigation. *Journal of Service Theory and Practice, 29*(4), 513-536. doi:10.1108/JSTP-03-2019-0067
Insights, O. (2019). *Government Artificial Intelligence Readiness Index 2019*. Retrieved from
Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255-260. doi:10.1126/science.aaa8415
Kepuska, V., & Bohouta, G. (2018). *Next-generation of virtual personal assistants (microsoft cortana, apple siri, amazon alexa and google home).* Paper presented at the 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC).
Kinsella, B. (2019). Australia leaps past U.S. in smart speaker adoption, Google home establishes dominant market share. Retrieved from https://voicebot.ai/2019/03/19/australia-leaps-past-u-s-in-smart-speaker-adoption-google-home-establishes-dominant-market-share/
Legg, S., & Hutter, M. (2007). Universal intelligence: A definition of machine intelligence. *Minds and Machines, 17*(4), 391-444.
Lin, J.-S. C., & Hsieh, P.-L. (2011). Assessing the self-service technology encounters: development and validation of SSTQUAL scale. *Journal of Retailing, 87*(2), 194-206.
Loiacono, E. T., Watson, R. T., & Goodhue, D. L. (2007). WebQual: An Instrument for Consumer Evaluation of Web Sites. *International Journal of Electronic Commerce, 11*(3), 51-87. doi:10.2753/JEC1086-4415110302
Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management, 80*, 36-51.
Lu, V., Wirtz, J., Kunz, W., Paluch, S., Gruber, T., Martins, A., & Patterson, P. (2020). Service Robots, Customers, and Service Employees: What Can We Learn from the Academic Literature and Where are the Gaps? *Journal of Service Theory and Practice*.
Malhotra, N. K., Nunan, D., & Birks, D. F. (2017). *Marketing research: An applied approach* (Fifth ed.). New York: Pearson.
Meyer-Waarden, L., Pavone, G., Poocharoentou, T., Prayatsup, P., Ratinaud, M., Tison, A., & Torné, S. (2020). How service quality influences customer acceptance and usage of chatbots? *SMR - Journal of Service Management Research, 4*(1), 35-51. doi:10.15358/2511-8676-2020-1-35
Mittal, B., & Lassar, W. M. (1996). The role of personalization in service encounters. *Journal of Retailing, 72*(1), 95-109.
Mogaji, E., Soetan, T. O., & Kieu, T. A. (2020). The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers. *Australasian Marketing Journal (AMJ)*.
Mori, M., MacDorman, K. F., & Kageki, N. (2012). The uncanny valley [from the field]. *IEEE Robotics & Automation Magazine, 19*(2), 98-100.
Morita, T., Kashiwagi, N., Yorozu, A., Suzuki, H., & Yamaguchi, T. (2019). Evaluation of a Multi-robot Cafe Based on Service Quality Dimensions. *The Review of Socionetwork Strategies*, 1-22.
Moussawi, S. (2016). *Investigating personal intelligent agents in everyday life through a behavioral lens.* (10165530 Ph.D.). City University of New York, Ann Arbor. ProQuest Dissertations & Theses Global database.
Mustak, M., Salminen, J., Plé, L., & Wirtz, J. (2021). Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda. *Journal of Business Research, 124*, 389-404.
Ng, A. (2019). AI for everyone. Retrieved from https://www.deeplearning.ai/ai-for-everyone/

Ng, S. C., Sweeney, J. C., & Plewa, C. (2020). Customer engagement: A systematic review and future research priorities. *Australasian Marketing Journal (AMJ).*

Novak, T. P., & Hoffman, D. L. (2019). Relationship journeys in the internet of things: a new framework for understanding interactions between consumers and smart objects. *Journal of the Academy of Marketing Science, 47*(2), 216-237.

Paluch, S., Wirtz, J., Kunz, W., Patterson, P., Gruber, T., Lu, V., & Martin, A. (2019). *Does C3PO really understand me? - Extending the service robots acceptance model*. Paper presented at the Frontiers in Service 2019, Singapore.

Pantano, E., & Pizzi, G. (2020). Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services, 55*, 102096.

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307-320.

Parasuraman, A. (2002). Service quality and productivity: a synergistic perspective. *Managing Service Quality: An International Journal, 12*(1), 6-9.

Parasuraman, A., Berry, L. L., & Zeithaml, V. A. (1993). More on improving service quality measurement. *Journal of Retailing, 69*(1), 140-147. doi:10.1016/S0022-4359(05)80007-7

Parasuraman, A., & Colby, C. L. (2015). An Updated and Streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research, 18*(1), 59-74. doi:10.1177/1094670514539730

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing*, 41-50.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing, 64*(1), 12.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994a). Alternative scales for measuring service quality: a comparative assessment based on psychometric and diagnostic criteria. *Journal of Retailing, 70*(3), 201-230.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994b). Reassessment of expectations as a comparison standard in measuring service quality: implications for further research. *Journal of Marketing*, 111-124.

Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of Service Research, 7*(3), 213-233. doi:10.1177/1094670504271156

Patton, M. Q. (2002). Qualitative research and evaluation methods. Thousand Oaks. *Cal.: Sage Publications*.

Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems, 25*(4), 145-181. Retrieved from http://proxy.library.adelaide.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=38418417&site=ehost-live&scope=site

Rai, A. (2020). Explainable AI: from black box to glass box. *Journal of the Academy of Marketing Science, 48*(1), 137-141.

Rank, J., Carsten, J. M., Unger, J. M., & Spector, P. E. (2007). Proactive customer service performance: Relationships with individual, task, and leadership variables. *Human Performance, 20*(4), 363-390.

Research, A. M. (2020). Intelligent Virtual Assistant (IVA) Market to grow at 33% CAGR during forecast period (2020-2025) - Insights on Growth Drivers, Size and Share Analysis, Key Trends, Leading Players, and Business Opportunities: Adroit Market Research. Retrieved from https://www.globenewswire.com/newsrelease/2020/02/24/1988963/0/en/Intelligent-Virtual-Assistant-IVA-Market-to-grow-at-33-CAGR-during-forecast-period-2020-2025-Insights-on-Growth-Drivers-Size-and-Share-Analysis-Key-Trends-Leading-Players-and-Busin.html

Robinson, S., Orsingher, C., Alkire, L., De Keyser, A., Giebelhausen, M., Papamichail, K. N., . . . Temerak, M. S. (2019). Frontline encounters of the AI kind: An evolved service encounter framework. *Journal of Business Research*.

Rosenbaum, M. S., & Russell-Bennett, R. (2020). Editorial: service research in the new (post-COVID) marketplace. *Journal of Services Marketing*.

Russell, S., & Norvig, P. (2016). *Artificial Intelligence: A modern approach* (Third ed.). Malaysia: Pearson.

Rust, R. T., & Huang, M.-H. (2014). The service revolution and the transformation of marketing science. *Marketing Science, 33*(2), 206-221.

Rust, R. T., & Oliver, R. L. (1993). *Service quality: New directions in theory and practice*: Sage Publications.

Seth, N., Deshmukh, S. G., & Vrat, P. (2005). Service quality models: a review. *International Journal of Quality & Reliability Management, 22*(9), 913-949.

Sheehan, B., Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research, 115*, 14-24.

Shell, M. A., & Buell, R. W. (2019). How Necessary Is the Human Touch? *Harvard Business Review, 97*(4), 28-28.

Siddike, M. A. K., Spohrer, J., Demirkan, H., & Kohda, Y. (2018). *People's interactions with cognitive assistants for enhanced performances.* Paper presented at the 51st Hawaii International Conference on System Sciences.

Sotiriadou, P., Brouwers, J., & Le, T.-A. (2014). Choosing a qualitative data analysis tool: A comparison of NVivo and Leximancer. *Annals of Leisure Research, 17*(2), 218-234.

Steinhoff, L., & Palmatier, R. W. (2020). Commentary: Opportunities and challenges of technology in relationship marketing. *Australasian Marketing Journal (AMJ)*.

Strauss, A., & Corbin, J. (1998). *Basics of qualitative research techniques*: Sage publications Thousand Oaks, CA.

Talwar, S., Talwar, M., Kaur, P., & Dhir, A. (2020). Consumers' resistance to digital innovations: A systematic review and framework development. *Australasian Marketing Journal (AMJ), 28*(4), 286-299.

Tam, J. L. M. (2012). The moderating role of perceived risk in loyalty intentions: an investigation in a service context. *Marketing Intelligence & Planning*.

Tan, C.-W., Benbasat, I., & Cenfetelli, R. T. (2016). An exploratory study of the formation and impact of electronic service failures. *MIS Quarterly, 40*(1), 1-29.

Thomaz, F., Salge, C., Karahanna, E., & Hulland, J. (2020). Learning from the Dark Web: leveraging conversational agents in the era of hyper-privacy to enhance marketing. *Journal of the Academy of Marketing Science, 48*(1), 43-63.

Troshani, I., Rao Hill, S., Sherman, C., & Arthur, D. (2020). Do We Trust in AI? Role of Anthropomorphism and Intelligence. *Journal of Computer Information Systems*, 1-11.

Tuu, H. H., Olsen, S. O., & Linh, P. T. T. (2011). The moderator effects of perceived risk, objective knowledge and certainty in the satisfaction-loyalty relationship. *Journal of Consumer Marketing*.

Van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers' Service Experiences. *Journal of Service Research, 20*(1), 43-58. doi:10.1177/1094670516679272

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management, 29*(5), 907-931.

Wu, P. C., Yeh, G. Y.-Y., & Hsiao, C.-R. (2011). The effect of store image and service quality on brand image and purchase intention for private label brands. *Australasian Marketing Journal (AMJ), 19*(1), 30-39.

Xiao, L., & Kumar, V. (2019). Robotics for Customer Service: A Useful Complement or an Ultimate Substitute? *Journal of Service Research*, 1094670519878881.

Xu, Y., Shieh, C.-H., van Esch, P., & Ling, I.-L. (2020). AI customer service: Task complexity, problem-solving ability, and usage intention. *Australasian Marketing Journal (AMJ)*.

Yang, R. (2018). Artificial Intelligence in Singapore: pervasive, powerful and present. Retrieved from https://www.businesstimes.com.sg/opinion/artificial-intelligence-in-singapore-pervasive-powerful-and-present

Yang, Z., Cai, S., Zhou, Z., & Zhou, N. (2005). Development and validation of an instrument to measure user perceived service quality of information presenting web portals. *Information & Management, 42*(4), 575-589.

Yang, Z., Jun, M., & Peterson, R. T. (2004). Measuring customer perceived online service quality: scale development and managerial implications. *International Journal of Operations & Production Management, 24*(11), 1149-1174.

Yin, R. K. (2009). *Case study research: design and methods*. Thousand Oaks, Calif.: Sage Publications.

Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting consumer responses to a chatbot on Facebook. *CyberPsychology, Behavior & Social Networking, 21*(8), 491-497. doi:10.1089/cyber.2017.0518

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *Journal of Marketing*, 2-22.

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing*, 31-46.

Zeithaml, V. A., Parasuraman, A., & Berry, L. L. (1985). Problems and strategies in services marketing. *Journal of Marketing*, 33-46.

Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2000). Conceptual Framework for understanding e-service quality: Implications for future research and managerial practice. *Marketing Science Institute*(00-115).

Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service quality delivery through web sites: a critical review of extant knowledge. *Journal of the Academy of Marketing Science, 30*(4), 362.

Table 1 Service quality dimensions in service environments

Research context (Human services)	Representative study	Dimensions	Applicability to AISA service context
Service quality of general service environments	Parasuraman et al. (1988)	Reliability, Responsiveness, Assurance, Empathy, Tangibles	AISA can provide human-like service performance to users in the context of various service industries. However, scale items are related to human service personnel and not for technology/online service environments represented by AISA.
Interpersonal service quality	Mittal and Lassar (1996)	Reliability, Responsiveness, Personalisation, Tangibles	Users may require AISA to communicate with social characteristics such as politeness and courtesy. However, similar to SERVQUAL, these scale items focus on human service interactions in the offline context and do not capture customisations which need to be performed in a technology/online context with AISA.
Retail (goods and services) service quality	Dabholkar et al. (1996)	Physical Aspects (Appearance, Convenience), Reliability (Promises, Doing it Right), Personal Interaction (Inspiring Confidence, Courtesy / Helpful), Problem Solving, Policy	User interaction with AISA may involve a variety of experiences found similarly in the retail context (e.g. interaction, fulfilment to problem solving). However, scale items are limited to offline retail store service experiences.
Call centre representative quality	Burgers et al. (2000)	Adaptiveness, Assurance, Empathy, Authority	Usage with AISA may contain dynamic voice-to-voice service enquiries, requests and interactions. However, input methods with AISA may also include text input (e.g. chatbots). Also, scale items are related to human call centre representatives.
Interaction quality, physical environment quality and outcome quality of service encounter with human service agent	Brady and Cronin Jr (2001)	Interaction Quality (Attitude, Behaviour, Expertise), Physical Environment Quality (Ambient Conditions, Design, Social Factors), Outcome Quality (Waiting Time, Tangibles, Valence)	Users may evaluate AISA based on dimensions related to interaction, environment and outcome factors at different stages of the usage experience. However, scale items are only relevant in an offline service context and not dependent on technology.
Research context (Technology services)	Representative study	Dimensions	Applicability to AISA service context
Self-service technology quality via cognitive or affective assessments	Dabholkar (1996)	Attribute-based: Speed of delivery, Ease of Use, Expected Reliability, Expected Enjoyment, Expected Control. Overall-affect: Attitude Towards using Technology Products, Need for Interaction with Service Employee	Users may obtain services by AISA independent of direct contact with human service agent. Also, they may evaluate AISA based on attribute and/or affective routes. However, AI advancements via machine learning can result in less-rigid service experiences compared to past self-service technologies relying on preprogramed outputs.
Online service quality involving variety of service processes (e.g. online banking)	Yang et al. (2004)	Reliability, Responsiveness, Competence, Ease of Use, Product Portfolio, Security	Users may require AISA such as a chatbots and virtual assistants to perform a variety of online service processes (including banking via chatbots). However, AISA are used in a variety of contexts beyond online banking.

Web portal quality	Yang et al. (2005)	Usability, Usefulness of Content, Adequacy of Information, Accessibility, Interaction	AISA such as chatbots and virtual assistants are internet-connected applications that provide information and communicate with users. However, scale items are limited to the web portal platform.
E-commerce service quality	Parasuraman et al. (2005)	Efficiency, System Availability, Fulfilment, Privacy	AISA are internet-connected digital applications that can facilitate user transaction via websites (e.g. chatbots). However, AISA can also provide information which may not relate to any commerce transactions. Also, scale items are limited to the e-commerce service context.
E-commerce service recovery quality	Parasuraman et al. (2005)	Responsiveness, Compensation, Contact	AISA may perform service recovery during or after service interaction to better deliver task performance. However, scale items focus on the service recovery context after an e-commerce transaction.
Website quality involving variety of tasks (i.e. information gathering, transacting, entertainment)	Loiacono et al. (2007)	Informational Fit-to-Task, Tailored Information, Trust, Response Time, Ease of Understanding, Intuitive Operations, Visual Appeal. Innovativeness, Emotional Appeal, Consistent Image, On-line Completeness, Relative Advantage	Users may seek specific information, perform transactions and/or engage AISA for its entertainment value in a digital context. However, scale items are limited to the website service environment.
E-retailing self-service quality	Ding et al. (2011)	Perceived Control, Service Convenience, Customer Service, Service Fulfilment	AISA are internet-connected self-service applications that can provide information and perform service delivery independent of direct contact with human service agent. However, scale items are limited to retailing experiences in an online context.
Self-service technology quality across various service industries	Lin and Hsieh (2011)	Functionality, Enjoyment, Security, Assurance, Design, Convenience, Customisation	Users may obtain services by AISA independent of direct contact with human service agent. Also, AISA as a form of self-service technology may be used across a range of service industries. However, service experiences by AISA are more flexible compared to past self-service technologies relying on preprogramed outputs.
Mobile commerce quality	Huang et al. (2015)	Virtual products: Contact, Responsiveness, Fulfilment, Privacy, Efficiency Physical products: Contact, Responsiveness, Fulfilment, Efficiency	AISA are internet-connected digital applications that can facilitate user transaction via mobile platforms (e.g. virtual assistants). However, scale items are limited to commerce services via mobile platforms.
Telematics service quality	He et al. (2017)	Efficiency, System Reliability, Information Quality, Security, Customisation, Call Centre Service	AISA are internet-connected digital applications that can be used for a variety of support services similar to telematics services (e.g. navigation, traffic situation, hands-free calling, driving supervision and diagnostics). However, beyond GPS navigation via smartphones or smart/autonomous vehicles, AISA can be found in other non-automotive service contexts (e.g. chatbots).

Table 2 Profile of interviewees

Identifier	Age	Gender	Location	Type	AISA familiarity context
CUA 1	38	M	Singapore	User	Chatbot user – Accessories
CUBF 1	24	F	Australia	User	Chatbot user – Beauty and food
CUF 1	35	M	Australia	User	Chatbot user – Finance
CUF 2	28	M	Australia	User	Chatbot user – Finance
CUF 3	35	M	Singapore	User	Chatbot user – Finance
CUF 4	34	M	Singapore	User	Chatbot user – Finance
CUF 5	40	F	Singapore	User	Chatbot user – Finance
CUF 6	35	M	Singapore	User	Chatbot user – Finance
CUF 7	32	F	Singapore	User	Chatbot user – Finance
CUGPS 1	37	F	Singapore	User	Chatbot user – Government and public services
CUH 1	52	F	Singapore	User	Chatbot user – Hospitality
CUH 2	29	F	Singapore	User	Chatbot user – Hospitality
CUMIT 1	43	F	Singapore	User	Chatbot user – Mobile and IT
CUMIT 2	28	M	Singapore	User	Chatbot user – Mobile and IT
VAUA 1	28	F	Singapore	User	Virtual assistant user – Alexa
VAUB 1	35	M	Singapore	User	Virtual assistant user – Bixby
VAUGA 1	30	M	Australia	User	Virtual assistant user – Google Assistant
VAUGA 2	49	M	Singapore	User	Virtual assistant user – Google Assistant
VAUGA 3	45	F	Singapore	User	Virtual assistant user – Google Assistant
VAUGA 4	36	M	Singapore	User	Virtual assistant user – Google Assistant
VAUGA 5	35	M	Singapore	User	Virtual assistant user – Google Assistant
VAUGA 6	31	F	Singapore	User	Virtual assistant user – Google Assistant
VAUGHM 1	43	F	Singapore	User	Virtual assistant user – Google Home Mini
VAUGHM 2	28	F	Singapore	User	Virtual assistant user – Google Home Mini
VAUS 1	28	F	Singapore	User	Virtual assistant user – Siri
VAUS 2	36	F	Singapore	User	Virtual assistant user – Siri
VAUS 3	37	M	Singapore	User	Virtual assistant user – Siri
VAUS 4	27	M	Singapore	User	Virtual assistant user – Siri
ARAAI 1	32	M	Australia	Expert	Academic researcher in applied AI
ARAAI 2	31	M	Australia	Expert	Academic researcher in applied AI
AIC 1	32	M	Singapore	Expert	AI consultant
AIC 2	33	F	Singapore	Expert	AI consultant
AIDS 1	35	M	Singapore	Expert	AI data scientist
AIDS 2	25	M	Singapore	Expert	AI data scientist
AIDS 3	25	F	Singapore	Expert	AI data scientist
AIDS 4	28	M	Singapore	Expert	AI data scientist
MLE 1	25	M	Australia	Expert	Machine learning engineer
Total interviewees					**37**

Table 3 Frequency of nodes coded in NVivo

Node	Frequency		Node	Frequency	
	Interviewees	Mentions		Interviewees	Mentions
Antecedents			*Outcomes: Cognitive*		
Design and technical aspects	18	28	Perceived value	5	8
Service quality dimensions			Brand image	9	18
Reliability	37	269	Psychological well-being	19	35
Responsiveness	34	116	*Outcomes: Affective*		
Availability	17	40	Satisfaction	6	10
Aesthetics	21	54	Subjective well-being	10	17
Personalisation	33	106	*Outcomes: Behavioural*		
Security	18	74	Continued use	10	17
Control	8	19	Good habits	3	7
Ease of Use	25	86	Laziness	5	5
Enjoyment	15	26	Productivity	22	46
Contact	10	23	*Situational and consumer-related factors*		
Proactiveness	28	84	Urgency	14	25
Anthropomorphism	24	60	Perceived risk	30	65
			Social norms	11	23
			Technology readiness	31	78
			Need for interaction	34	76

Note: Table 3 reports the frequency of nodes by the number of interviewees (out of a total 37 interviewees) who mentioned the nodes and the total number of node mentions by all interviewees as coded in NVivo.

Table 4 Data structure containing key constructs and illustrative quotes

1st order concepts	2nd order themes	Aggregate dimension	Illustrative quotes
AISA correctly recognises user command.	Command Recognition	Reliability	"Because maybe it doesn't recognise my enunciation well, or maybe in terms of who I have in my contact list… so, it called the wrong person... that was quite odd. So, I had to cancel the call pretty quickly." (VAUS 2)
AISA understands command meaning.	Intent Recognition		"You must make it be able to understand intent very quickly and give it the agency to resolve the intent." (AIDS 2)
AISA delivers the service as promised.	Task Fulfilment		"By the end of the month, I actually received my bill. And it shot up to about two to three times. And I was informed that actually the chatbot didn't give me the correct recontract deadline. So, it didn't end really well for me because I had to pay two times more than what I have to pay every month." (CUMIT 2)
AISA is responsive when invoked.	Prompt Response	Responsiveness	"I expect them to respond in a timely manner… about one to two seconds… so that is an expectation of them as an AI." (VAUA 1)
AISA completes the task quickly.	Quick Resolution		"The number one thing is speed; to resolve your query as soon as possible. Because a lot of the times AI has to ask ten surrounding questions before they can pinpoint the correct path to the user or whatever. So, I think speed and efficiency, that's probably the key characteristics that's good service on the consumer's side." (MLE 1)

AISA is available on demand 24/7.	Time Availability	Availability	"But chatbots - 24/7. So, it basically bridges the time gap in globalisation, in a globalised world. Irrespective of what time zones you are, chatbots are there." (CUF 1)
AISA can be accessed in many places.	Place Availability		"Perhaps in the future…it needs to everywhere right… maybe in the cars… maybe be in public transport services. So, the technology can be everywhere." (VAUS 1)
AISA is appealing to users.	Aesthetical Appeal	Aesthetics	"Interface wise, as long as it tells you this is a chatbot. But you don't really have to put a lady there or a very huge figure to tell me this is a chatbot; this is a quite irritating, actually." (AIC 2)
The clarity of information due to the interface design of the AISA.	Aesthetical Functionality		"The noise…And then I just hear a 'Bing' and I'm like 'Where did that come from?'. And then sometimes you leave the website open and the chatbot, within five minutes, asks you 'Can I help? Can I help?'. So, and that's a little bit of... if I need your help, I will type something." (CUBF 1)
AISA adapts according to context.	Adaptiveness	Personalisation	"More towards like it can read my mind…maybe if it's towards the night, then if I call it out… then it knows that I'm looking out for some alarm…" (VAUB 1)
AISA gives warm attention to user.	Empathy		"I want the person to tell me or make me feel comfortable why I should hear to the doctor - why that ointment is really good and what I'm not looking at; AI can't do that according to me." (CUF 1)

User comfort in sharing personal information to AISA.	Privacy	Security	“I think if it's more sensitive I'd rather speak to someone because I don't want to give all these details online through a chatbot.” (CUF 7)
User confidence in how personal data will be used and protected by AISA.	Data Access and Protection		“Everything is being captured. So how would you know what is being protected in there?... What are you revealing to the company?” (AIC 2)
No unwelcomed performance anomalies by AISA.	Intrusion		“If it starts promoting random things to me or giving me information that necessarily I didn't ask, but is meant to influence me, I would potentially immediately get rid of it… Now you're trying to get to influence my behaviour instead of actually trying to aid it in some way possible.” (VAUGA 1)
User feels in control of AISA.	User Control	Control	“Another one is maybe if we have a choice... if we can amend its settings to sync with certain sources of data that we prefer?” (VAUGA 3)
User can command AISA in different ways.	Command Methods	Ease of Use	“I feel like if the chatbot is multilingual, then it is an added value.” (AIC 1)
User knows how to use AISA.	Usage Knowledge		“Or maybe it's the way I use it is wrong, but I don't know. I've been trying to figure this out for a long time.” (VAUGHM 2)
AISA can be used with other applications.	Technology Interaction		“But because of the brand being tied to certain integrations...so, I have a disconnected home... I wish I can just tell Siri ‘Hey Siri, turn on my Dyson’; I can't do that, because Dyson only works with Alexa.” (VAUS 3)
User finds the AISA interesting to use.		Enjoyment	“I think the Winston-like capability is interesting simply because I think there's a lot of experiential opportunities that we, as a person walking down the street, we miss out simply because we are not aware.” (VAUGA 2)

User has ability to contact human service agent when required.	Contact by User	Contact	“If the AI service agent chatbot cannot quite answer our questions satisfactorily, what happened here is that they should have a button ‘Does the chatbot answer your question satisfactorily or not?’ You can click yes or no. Then if you click no, they must give us an option to speak directly with a human being.” (CUF 4)
Human service agent contacts user to offer better resolution related to service task.	Contact by Organisation		“If the chatbot is smart enough to say ‘Okay, I think agent X will call you to help you on this’... And the agent calls and knows all the information that has been given to the chat engine. And he just directly tries to address the query... the customer is happy with that.” (AIC 1)
AISA is resourceful in offering relevant information and alternatives.		Proactiveness	“I really appreciated the time when I actually asked for A and then they also gave me A and B after… which at that time, I didn't think about it… so being able to anticipate was something that I appreciated. And I would call it service performance.” (CUF 7)
AISA feels like a human.	Abstract Anthropomorphism	Anthropomorphism	“So that was a very pleasant experience because I really thought that it was a human being doing that. Only then did I realise that it was literally a whole ecosystem of chatbots - there was no human being behind it.” (CUA 1)
AISA appears like a human.	Non-Psychological Anthropomorphism		“She does speak to me like a personal assistant. But with a face on it, it feels like you're talking to a real person. So that makes it more real-life like… would give me an assurance.” (VAUS 4)

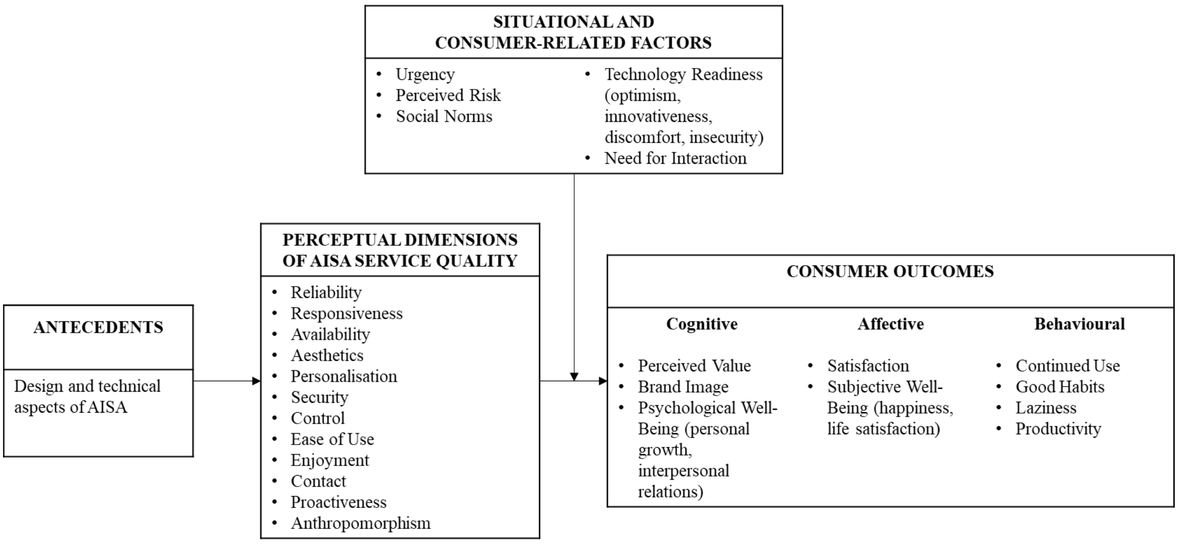

Fig. 1 Conceptual framework of AISA service quality

Table 5 Illustrative research questions pertinent to AISA service quality

AISA Service Quality Factors	Consumers	Service Firms	Society
Perceived AISA Service Quality Dimensions	• How do consumers feel about incorporating more AISA in their lives and under what conditions will consumers trust AISA more in providing service? • How is the 'uncanny valley' phenomenon manifested in service settings, what are the implications for AISA service quality, and how do they change across types of services and AISA? • How does the relative importance of the different AISA service quality dimensions differ across various types of services for consumers? (E.g. would they differ for high involvement decision making such as healthcare services?)	• What is the role of human service employees where AISA are used for service? How has the role of human service employees changed with greater presence of AI in services? • How can service firms effectively improve AISA service quality (e.g. training AISA) continuously? • Will pervasive use of AISA entail the emergence of service quality standards, and if so, how can service firms measure and improve how their AISA meet these standards? • How should service firms communicate their data policies to the consumers to counter privacy issues?	• To what extent can society influence service quality expectations and performances of AISA? • Should the governance of AISA service quality be left to service firms alone or involve other stakeholders? • What are the implications of AISA for privacy since extent to which AISA achieves outcomes depends on how much data it has been given?
Consumer Outcomes of AISA Service Quality	• How is customer satisfaction affected when consumers transition from human service providers to AISA service providers (i.e. when tasks once performed by humans are now provided by AISA)? • How and to what extent does anthropomorphism in AISA influence trust, loyalty and well-being? • Do consumers form emotional bonds with AISA and if so, how are they affected by AISA service quality?	• How does AISA service quality influence the branding (e.g. brand image, brand personality, brand attachment) of the service firm? • How can service firms responsibly facilitate the use of AISA by consumers? • What are the alternative uses of the data that is captured and created by AISA, and how can service firms use the data more effectively?	• Do AISA exhibit bias and/or inequality? How do we minimise ensuing consumer vulnerability? • As the knowledge of AISA and use grows, how will established traditional views of expertise and wisdom change? • What are the broader externalities (e.g. social cost) that are associated with the greater use of AISA? • What are the unanticipated consequences of the broader use of AISA?

AISA Service Quality Factors	Consumers	Service Firms	Society
Antecedents /Situational and Consumer-Related Factors of AISA Service Quality	• How do the different representations of AISA (i.e. physical or virtual forms) affect AISA service quality? • In what contexts are humanlike qualities of AISA valued by consumers? • How does consumers' evaluation of AISA service quality differ for different types of consumers (e.g. demographic, psychographic and technographic characteristics)? • What hopes and fears do consumers have about greater availability of AISA in service?	• How will the nature of AI technology affect the manner in which service firms adopt it for service provisioning? • How can service firms enhance consumer trust to increase AISA service quality perceptions?	• Under what conditions will the use of AISA become a social norm? • How will society's attitudes towards AISA change and how will this affect AISA service quality expectations?