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Artificial Intelligence Service Agents: Role of Parasocial Relationship

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Increased use of artificial intelligence service agents (AISA) has been associated with improvements in AISA service performance. Whilst there is consensus that unique forms of attachment develop between users and AISA that manifest as parasocial relationships (PSRs), the literature is less clear about the AISA service attributes and how they influence PSR and the users' subjective well-being. Based on a dataset collected from 408 virtual assistant users from the US, this research develops and tests a model that can explain how AISA-enabled service influences subjective well-being through the mediating effect of PSR. Findings also indicate significant gender and AISA experience differences in the PSR effect on subjective well-being. This study advances current understanding of AISA in service encounters by investigating the mediating role of PSR in AISA's effect on users' subjective well-being. We also discuss managerial implications for practitioners who are increasingly using AISA for delivering customer service.

Keywords

Artificial intelligence, anthropomorphism, enjoyment, subjective well-being, parasocial relationship

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I. Introduction

Artificial intelligence service agents (AISA) are AI-based applications, machines and robots that can learn from experience and improve their service performance.[1] AISA such as virtual assistants[2] and physical social robots[3] have demonstrated a capability to deeply integrate into service delivery[4] and offer high quality service, often comparable or even superior to human service employees.[5,6] Consequentially, AISA are broadly seen to have a strong potential to revolutionize the service industry.[7-9] There is growing evidence that service providers are deploying AISA to build and manage customer relationships.[10,11] AISA adoption growth is forecast to between 14% and 33% for the market value of AISA from 2021 to 2025.[12,13]

Increasing consumer interaction with AISA, in combination with rapid advances in AI innovation, are enhancing AISA service performance.[14] With continued use, consumers can actively contribute to AISA's service performance improvement; due to AISA's ability to learn from consumer's past behavior, they can adapt and improve future service performance (e.g. offering more personalized service).[7] In addition, as AI technology advances, service providers are expected to have greater access to more sophisticated AISA which can be used to offer more efficient and personalized service solutions to consumers.[15] This is expected to enhance AISA's performance capabilities and scope of contribution to AI-enabled services.[16]

Notwithstanding the importance of AISA's utilitarian benefits,[17,18] advancements in AI are also enabling AISA to provide hedonic outcomes, such as empathy reactions to consumer's emotions.[5] Research has found that such reactions can evoke a sense of attachment with AISA for some consumers.[19] For instance, some consumers have reported imagining having intimate sexual relationships with their virtual assistants such as Siri, Google Assistant and Alexa, with over a third wishing that their virtual assistants were real people.[20] Whilst research into the nature and implications of such emotional relationships to a non-human entity such as AISA have gained attention in recent literature,[21,22] more research has been called for to better explain the effects of AISA on consumer's well-being perceptions.[7,23,24]

We draw on the parasocial relationship (PSR) theory to investigate how AISA affect the consumer's PSR with their AISA and the consumers' subjective well-being. First introduced by Horton and Wohl[(25)] and Horton and Strauss[(26)], PSR is defined as the emotional bond that people develop with a character (e.g. media performer). Building on this notion, we argue that the salient attributes of AISA service, namely anthropomorphism and enjoyment AISA use offers to consumers, can enhance the consumer's PSR with their AISA. Accordingly, we develop and test a model that explains how these AISA attributes can affect consumers' subjective well-being and the role that PSR plays in this relationship.

We make the following two key contributions. First, our theoretical model features the mediating role of PSR in the AISA context. This advances our understanding of AISA, PSR, as well as the relationship between them. Existing research underscores the increasing significance of AISA[8] and PSR in service delivery,[27] but falls short of explaining the nature of their roles and related implications. In addressing this shortcoming, our study goes beyond traditional service outcomes, such as satisfaction and loyalty[28] to explain the specific role that PSR plays and how it is activated by consumer perceptions of AISA attributes. In addition, our research contributes to PSR theory by identifying anthropomorphism and enjoyment as new antecedents to PSR.[29]

Second, our empirical investigation advances the understanding of how consumer well-being can be affected by AI-enabled services.[30] We note that existing research appears to have a dominant focus on the service providers' viewpoint, specifically looking at the importance of achieving service outcomes, such as customer satisfaction, perceived value and loyalty,[28] as means of advancing their commercial interests.[31] In PSR studies, researchers have also shown how an increase in PSR can positively influence the continued use of technology platforms.[27,32] However, scholars continue to call for more research looking at the role of services in affecting the well-being of consumers.[30,33] While service research has made important inroads in this area,[34,35] our study extends this line of research by investigating how service can improve consumers' wellbeing in the emerging and increasingly relevant AISA service environment.[7,24]

The remainder of the paper is structured as follows. We begin with an overview of the AISA research landscape by introducing a classification mapping various AISA types. We proceed with a discussion of PSR theory and related research, AISA attributes and subjective well-being which we use as a basis to develop a research model. This discussion culminates with our hypotheses. We show how the AISA service attributes can activate PSR. We then discuss the method used to collect data to test our theoretical model and hypotheses using virtual assistants as a common type of AISA. We conclude the paper with a discussion of our findings, theoretical and managerial implications, limitations and future research.

II. An AISA Classification

AISA's learning capability, in comparison to other types of technology-based self-service, allows them to successfully perform increasingly more complex service tasks.[5] There is evidence that AISA can perform some services better than humans and non-AI self-service technology.[6,36] On the one hand, AISA are potentially less limited by prejudices and the relative inefficiency compared to humans. As such AISA can conduct certain aspects of service delivery more efficiently than service employees.[6] On the other hand, in comparison to non-AI self-service technologies that are typically rigid in following specified interaction scripts, AISA can adapt and as a result, offer greater scope for customized social engagement and personalization to consumers in service encounters.[6, 22]

While these characteristics apply to a broad spectrum of AISA, it is important to differentiate these applications as more are developed and become available for use in the market. AISA can be categorized based on their perceived primary benefits (i.e. utilitarian vs hedonic) and their form (i.e. virtual vs physical). Consumers' affective responses towards AISA also differ. Thus, we map the AISA landscape based on how consumers generally value an AISA application in the utilitarian-hedonic spectrum[5] and whether they are predominantly virtual or physical in representation.[6,7]

[Insert Figure 1 here]

Consumers place primary value on AISA's hedonic factor when the AISA is primarily designed to provide affective service.[37] They are designed with varying purposes and play increasingly important roles such as supporting consumers in changing their behaviors,[38] or assisting the elderly in their living environments.[39] For instance, social robots such as Pepper are developed to converse with consumers and keep them company in aged care and schools.[40] Pepper is also mainly classified as a physical AISA despite having virtual text displays which are used to interact with consumers.[40] Physical representation can create relatively higher affective responses from users than virtual AISA.[41] Thus, we expect that AISA which are mainly designed to meet the hedonic needs of consumers and that have a more physical representation are likely to evoke high affective responses from consumers, as shown in Figure 1.

Nonetheless, many consumers have turned to virtual forms of AISA, such as the companion chatbot Replika[42] and virtual assistants including Siri, Alexa and Google Assistant,[43] to address their hedonic needs due to their greater availability and convenience to access. These AISA are predominantly voice or text-based activated and are widely accessible via smartphones (e.g. Siri, Google Assistant, Replika) and internet-connected devices (e.g. Alexa, Google Home Mini).[44] They can offer hedonic benefits to consumers, such as having conversations and telling jokes.[44] Accordingly, virtual assistants have capacity to offer hedonic functionality to consumers. It is therefore possible for consumers to form emotional relationships with their virtual assistants.[20] Due to the wide popularity and availability at the time of this study, we selected virtual assistants as a suitable AI application type representing AISA in our research.

III. Theoretical background and Hypotheses Development

Parasocial Relationship

The PSR conceptualization was originally developed to describe the illusionary bond that viewers form with characters played by performers in media such as television and theatre.[25] Despite this quasi-relationship being one-sided and lacking any real, humanlike reciprocation, spectators can be influenced by a performer through the performer's persona in their role.[25] This enduring relationship can develop over multiple parasocial interactions which are short-term encounters in which the viewer experiences a sense of immediacy to respond and participate with the performer.[25,26,45] That is, PSR can exist beyond the moment of interaction[46] and is concerned with the longer term relationships viewers can form with a performer.[47] In the AISA use context, AISA plays the role of the performer.

In terms of interaction, the one-sided bonding that is PSR can be triggered by both actual non-interaction (e.g. actors on television screen) and with actual interaction (e.g. a talk show host mingling with his audience).[25] The latter constitutes a more explicit form of parasocial interaction (i.e. a perception of intimate communication albeit only by one party in reality) which can nonetheless lead to PSR.[26] One-to-one communications can be termed parasocial if the persona cannot address each audience member.[26] Specifically, Hartmann[(48)] suggests that interactive encounters may be considered to be parasocial even when they are with *artificial agents* since such entities are nonetheless *perceived* to be social beings. Accordingly, we argue that the personal bond that AISA users may experience with AISA can be of a parasocial nature, since AISA do not experience the emotional bond in return, and there remain limits to the ability of an AISA to *truly feel* and cater to the individual interaction nuances of multiple user profiles.[10]

Beyond celebrities and fictional characters, the concept of PSR has been extended and measured for other types of personas[25] including race car drivers,[49] social network connections[50] and live-streaming gamers.[32] Social, task and physical attraction to the persona have been identified as factors driving the form of a PSR[29] and have been widely accepted in the literature.[27,51] Consumers can also develop PSR with inanimate target personas, such as puppets[25] and AISA such as virtual assistants[27] due to their anthropomorphic attributes. Thus, the AISA attribute of anthropomorphism can be a PSR trigger.

AISA Attributes

Prior technology adoption research has identified a number of factors that drive AISA adoption and continued use. For example, consistently with Lu et al.,[(52)] Gursoy et al.[(53)] identified six major predictors of consumers' willingness to accept AI devices in service delivery: performance efficacy, hedonic motivation, anthropomorphism, social influence, facilitating condition, and emotion. In the context of service robot adoption, perceived usefulness, social capability, and device appearance are the key drivers.[54] Niemelä et al.[(55)] found that hedonic motivation is the primary factor influencing customers' behavior-intention of using AI devices in retail stores. However, these studies only investigated consumers' willingness to adopt the AI devices whilst the full extent of impact of using AI devices or applications remains unknown.

Building on these adoption studies, we argue the affect related drivers of adoption may also contribute to users' wellbeing. In particular, prior research focus on the salient attributes of anthropomorphism and hedonic experience or enjoyment of using AISA suggest that in addition to utilitarian benefits, consumers value the ability of AISA to meet their hedonic needs.[1] We posit that anthropomorphism and enjoyment act as key drivers to PSR which in turn leads to subjective well-being. We explain this position in the following subsections which culminate with the argument that PSR is activated by the cumulative effect of anthropomorphism and enjoyment.

Anthropomorphism is a key characteristic that distinguishes AI from non-AI applications and a salient attribute of AISA.[6,56] It describes the attribution of human capacities to non-human agents, specifically referring to the attachment of human-like characteristics to AISA. Indeed, similar to television characters that create the illusion of intimacy through gestures and other communication cues,[25] AISA have a wide range of interface designs that can mimic human traits, such as voice.[57]

Prior information systems (IS) research suggests that a consumer can develop perceptions of a social presence when interacting with an anthropomorphic AI application.[58] Such responses can occur as a result of human capacities and characteristics, including human-like communication or features. This perception of social presence is similar to the PSR phenomenon in which viewers form hedonic connections with their television characters.[58] Conceptually, the social attraction element of PSR corresponds directly to the anthropomorphic characteristics of AI[27] which motivate ongoing use of the application. Perceptions of AISA's social attraction, which include the humanness of the interaction experience, have been shown to be positively associated with PSR.[27]

In addition to the abovementioned evidence in the IS literature, PSR theory is also helpful in explaining the relationship consumers form with brands. Conceptually, PSR adequately captured the nature of this affective attachment which is one-sided towards an object (i.e. brand) that is inanimate and anthropomorphic.[59] Following this line of argument, it is reasonable to posit that consumers are likely to develop PSRs with an AISA that is inanimate and anthropomorphic similar to the way they develop PSRs with a media character or a brand. Based on these arguments, we hypothesize that:

H1. AISA's anthropomorphism positively influences the consumer's parasocial relationship with AISA.

Perceived enjoyment is the perceived pleasure an individual is expected to experience from using an AISA. Enjoyment or hedonic motivation has consistently been found to be the primary predictor of consumer technology acceptance and adoption behavior.[60-62] Prior research indicates that enjoyment leads to positive behavioral consequences with respect to the intention to use technology,[63,64] intention to purchase virtual goods in a game,[65] and intention to shop online.[66]

AISA have been reported to satisfy one's need for novelty and entertainment.[67] While the level of enjoyment has been shown to be significantly correlated with the level of happiness in non-AI contexts, we argue that this relationship is mediated by PSR in the AISA context. Customers who believe that using AI devices is fun and interesting are likely to develop PSRs with AISA. There are two possible explanations for this phenomenon. First, high level of hedonic motivation may bias the general evaluation of an AISA based on the cognitive dissonance theory, resulting a more favorable general attitude which forms the foundation of an affective bond with the AISA. Second, the AISA is not merely acting as an intermediary to facilitate a relationship between the consumer and other humans, but is rather the target of the relationship formation itself.[68] Similar to the way that enjoyment leads people to engage in PSRs with a performer, it is reasonable to expect an affective bond forming as a result of enjoyable moments of interactions between the user and AISA. Accordingly, we argue that the consumers' feeling of enjoyment experienced whilst interacting with an AISA can result in an increased emotional bond with their AISA. The development of PSR is reinforced by multiple, ongoing interactions with AISA. The accumulation of such frequent parasocial interactions, which are anchored by degrees of enjoyable moments, can lead to PSR.[45] Thus, we hypothesize that:

H2. Enjoyment in using AISA positively influences the consumer's parasocial relationship with AISA.

Subjective Well-being

Subjective well-being refers to the evaluation that people have of their own lives.[69] This self-assessment can be cognitive (e.g. life satisfaction) or affective (e.g. moods and emotions).[70-72] Various scales have been developed in the literature to measure these cognitive or affective components,[73,74] including the 'satisfaction with life' scale[71] and 'subjective happiness' scale.[75] The hedonic focus of measuring subjective well-being fits within our study context of affective outcomes arising from consumer interactions with the service environment,[70] and has been applied in past service studies.[35] Subjective well-being has been put forth as an important research area due to the increasing permeability and impact of service systems in the consumers' lives.[76-79]

As technology becomes more integrated into service[80] and an array of technologies including AISA are introduced into the service industry,[8] it is also critical to assess how well-being can be affected with the use of these applications in service. The association between technology and well-being may be negative if the user is unsure of how to use a complex system,[81] or positive if the technology facilitates continued interactions.[82] PSR resulting from AISA is unique in its resemblance to a real social relationship and can involve more emotional connections with consumers.[15,22]

Beyond professional social support services, general supportive interactions with others can improve a person's subjective well-being.[83] PSR attachments are a means to experience such social relationships,[25] and can also impact the person's overall affective state.[46] Hence, we hypothesize that:

H3. Parasocial relationship with AISA positively influences a consumer's subjective well-being.

Gender and Length of Use

Consumers of different demographics tend to place different emphasis on hedonic benefits associated with technology[60] including AISA.[43] Specifically, gender differences have been found in prior studies of technology adoption behavior. For instance, Gefen and Straub[(84)] found that females experienced a higher perceived social presence with emails as well as greater perceived usefulness, while males may feel more at ease with using technology as compared to females. Venkatesh et al.[(60)] also showed that the impact of habit on the intention to use technology is stronger for males than females.

Indeed, issues of gender in AI assistant design have triggered much debate in recent years as more consumers adopt AI voice assistants. Many questions have been raised by researchers and academics when examining the phenomenon and confronts these views with discussions around the feminization of AI. In the context of computer-embodied voices, human gender stereotypes apply - male voices are found to be more dominant, forceful, and assertive. This partly explains why female voices are selected for AISA such as Alexa, Siri and Google Assistant. However, this phenomenon remains an open question and subject of further theoretical and empirical enquiry.

For our specific study, we expect gender differences in AISA usage. From a social psychology perspective, male users are generally more pragmatic and highly task- and result-oriented than females.[85] Social role theory suggests that females are characterized by emotional traits while males exhibit instrumental traits. In addition, gender differences are evident in terms of general attitudes and behavioral intention towards AI technology and robotics in particular. Not surprisingly, due to a stronger need for social connection and technology anxiety, Japanese females are found to anthropomorphize robots more strongly than Japanese men.[86] Similarly, earlier research looking a gender difference and PSR found that females are more likely to report formation of parasocial relationships with media celebrities or characters than males.[87] Thus, it is not unreasonable to argue that the emotional connections and social support conjured from PSR are more likely to influence females' subjective well-being than for males. That is, females may experience stronger effects of PSR than males while using AISA.[88]

Like social interaction, PSRs become stronger when more interaction occurs. AISA have the ability to learn quickly from past interactions and historical information[5,9] which in turn enable them to manage interactions in service encounters with greater scope and complexity relative to the specific, predefined interaction scenarios that are typically managed by traditional service technologies such as SSTs.[89-91] We argue that as customization and personalization are strengthened in users' interactions with AISA, affective bonds with AISA would increase, ultimately influencing one's overall affective state. Hence, we expect the extent to which PSR influences the user's subjective wellbeing depends on the length of AISA experience. Hence, we hypothesize that:

H3a. The positive impact of parasocial relationship on subjective well-being is stronger for female than for male users.

H3b. The positive impact of parasocial relationship on subjective well-being is stronger for users with longer AISA experience than for users with shorter AISA experience.

The theoretical framework integrating our proposed interrelationships between the variables discussed in this section is shown in Figure 2.

[Insert Figure 2 here]

IV. Methodology

Construct Measurement

The measures used in this study were adapted from previous constructs in the literature. Anthropomorphism was measured by adapting items developed by Moussawi and Koufaris(92) and Bartneck et al.(93) While items from Moussawi and Koufaris(92) were developed for virtual assistants, our study wanted to ensure that the constructs used could also be applied across other AISA types as depicted in our AISA classification in the earlier Figure 1. Accordingly, items from Moussawi and Koufaris(92) which tap onto the personality aspects of AISA ("The personal intelligent agent can be happy/friendly/respectful/funny/caring") were collapsed into a single measure item "The AISA has personality", whereas items associated with behavior

("The personal intelligent agent can feel love/get upset at times/get frustrated at times") were collapsed into the measure item "The AISA is able to behave like a human". We also turned to the Godspeed Questionnaire Series by Bartneck et al.[(93)] which is one of the most frequently used, widely validated scales in human-robot interaction [94] and which continues to be used in recent research.[95] Specifically, one item from the anthropomorphism scale of Bartneck et al.[(93)] that was worded most appropriately to measure the humanness of the AISA was also adapted as the measure item "The AISA has humanlike features". Facets from the other items in their anthropomorphism scale were already captured in our existing item measures or could not be appropriately generalized across other AISA types (e.g. "Moving elegantly"). Overall, by reducing the complexity and scale length while still retaining the meaning of the intended item measures, greater construct clarity could also be reached.[96] Our resulting anthropomorphism construct was also reliable and valid with sufficient psychometric properties (see later section on Model Evaluation). For enjoyment, we used the expected enjoyment scale from Dabholkar.[(97)] To measure PSR, we adapted five of the six items from the positive PSR sentiments on virtual friendship by Hartmann et al.[(49)] that were appropriate to the AISA context. Finally, subjective well-being was measured using three items from Su et al.[(35)] While these scales were originally developed in different contexts, they demonstrate consistent reliability in measuring the intended target constructs. For example, items in the enjoyment scale, which was developed to measure the pleasure of using touch-screen kiosks, demonstrate sound reliability and validity when measuring the pleasure that consumers experience from using technology and have been featured in many contexts such as e-service,[98] social media,[99] and virtual assistants.[100] Table 1 details all the item measures used in our study.

[Insert Table 1 here]

Data Collection

A self-administered survey was distributed using the online panel company Qualtrics to virtual assistant users from the USA. Purposive sampling was used with the survey participation dependent on the respondents having prior experience interacting with virtual assistants in the last three months. To ensure that respondents were clear on the AISA usage context (i.e. virtual assistants), examples of different types of virtual assistants were provided in the survey introduction in the form of illustrating images. The use of Qualtrics also allowed the questionnaire to be further customized to a more familiar scenario based on the choice of virtual assistant that was indicated by the respondents. For instance, Alexa users would answer the question "Alexa has humanlike features", while Siri users would instead respond to "Siri has humanlike features" in the survey. The sample was sourced from the US since it represents one of the top 10 countries with a significant number of AISA users[101] and is expected to continue to lead the global market share for virtual assistants.[13]

The questionnaire consisted of two sections. The first section contained demographic and AISA usage questions including screening questions on their AISA usage to ensure that respondents met the participation criteria (i.e. i) Individuals 18 years and above, ii) US residents and iii) used virtual assistants in the past 3 months). In the second section, respondents were asked to rate the construct item statements in Table 1 using a seven-point Likert scale anchored from 1 = strongly disagree to 7 = strongly agree. Construct items were shown in random order to the respondents.

Several measures were taken to improve overall response quality. First, we included one instructional manipulation check[102] at the beginning of the survey which instructed participants to select "Others" to a question "Any other comments before we proceed with the survey". To reduce common method bias, several procedural remedies as recommended by

MacKenzie and Podsakoff[(103)] were factored into our survey, including enhancing cognitive effort by explaining to respondents how their responses will benefit the study, and encouraging true responses by describing procedures to ensure anonymity. At the beginning of the survey, respondents were also informed that formal ethics approval was obtained for the study from the authors' affiliated university. In addition, straight-lining problems with participant responses were also addressed. Specifically, responses containing identical or nearly identical response categories to the questionnaire items were removed.[104]

The final sample gathered from Qualtrics which satisfied the data requirements consisted of 408 responses with an almost even gender split (male=49.8%, female=50.2%). Half the respondents used their AISA on a daily basis (50.0%) while about one-third did so weekly (32.4%). Majority of respondents (52.2%) had also used their AISA for 1-3 years. Alexa, Google Assistant and Siri were three most popular types of virtual assistants used which mirrors the virtual assistant usage trend amongst the US population.[105] Table 2 summarizes the profiles of respondents for the survey.

[Insert Table 2 here]

V. Analysis and Results

Model Evaluation

The psychometric properties of our study model were assessed using the Partial Least Squares Structural Equation Modelling (PLS-SEM) via the software package SmartPLS 3. The PLS-SEM method has been used in IS research and is well-suited for exploring and predicting new theoretical relationships between variables.[106] In addition, as the mediating role of PSR is of significance to our study, the PLS-SEM method offers the advantage of establishing mediation effects without the need for a separate mediation analysis using the PROCESS macro in SPSS [107]. Accordingly, the software package SmartPLS 3 was used to execute PLS-SEM rather than SPSS AMOS which is also more appropriate for Covariance-Based Structural Equation Modelling.[106]

The advocated two-step model assessment procedure consisting of evaluating the outer measurement model before testing the inner structural model was used for our study.[108] In terms of model fit, the applicability and reliability of different goodness-of fit measures for PLS-SEM remain debated and cautiously advocated in the literature.[109,110] Accordingly, the frequently used Standardized Root Mean Square Residual (SRMR) heuristic for PLS-SEM[111] was employed for our model. Confirmatory factor analysis resulted in an SRMR value of .05 which met the suggested threshold of .08.[112]

Next, we evaluated the PLS-SEM measurement model for reliability and validity.[106] For internal consistency reliability, all Cronbach's alpha and composite reliability values satisfied the recommended threshold of .70.[113] As for convergent validity, all average variance extracted (AVE) values exceeded the minimum cut-off of .50.[114] In terms of indicator reliability, all factor loadings satisfied the ideal criteria of .70.[113] Table 3 summarizes the reliability and convergent validity results of the measurement model.

[Insert Table 3 here]

For discriminant validity, all values of the Hetero-Trait Mono-Trait (HTMT) ratio of the correlations were found to meet the conservative cut-off of .85, indicating discriminant validity[115] (see Table 4).

[Insert Table 4 here]

Common Method Bias Testing

In addition to procedural remedies, statistical remedies were employed in our study to further mitigate common method bias. First, using Harman's single-factor test, none of our model factors accounted for more than 50% of the covariance among items.[116] In addition, using the guidelines by Kock,[(117)] the variance inflation factor (VIF) values from a full collinearity test were lower than the threshold of 3.3. Both tests suggested that common method bias remained undetected in our study.

Hypotheses Testing

Having assessed our measurement model to be satisfactory, we proceeded to assess the structural model and conducted path analysis. The statistical significance of the weights in the analysis was achieved through a bootstrapping procedure with 5000 samples using a two-tail test at 95% significance level. As shown in Table 5, there was a significant and positive relationship between anthropomorphism and PSR (β=.50, $p < .001$), thus supporting H1. There was also a significant and positive relationship between enjoyment and PSR (β=.26, $p < .001$), supporting H2. Upon analysis, the strength of correlation between anthropomorphism and PSR was almost twice compared to enjoyment and PSR. Finally, there was a significant and positive relationship between PSR and subjective well-being (β=.31, $p < .001$), supporting H3.

[Insert Table 5 here]

To test H3a and H3b, we conducted a multi-group analysis to assess if the path coefficient between PSR and subjective well-being varied according to the demographic variables of respondent's age and the length of time using AISA. Using a median split, contrary to our hypothesis, results indicated that the effect was significantly higher for males than females (β difference=.19, p difference < .05), thus rejecting H3a. However, the effect between PSR and subjective well-being was significantly higher for those who had used their AISA for 4 years and above compared to those who had used AISA for less than 4 years (β difference=.24, p difference < .01), thus supporting H3b. These results will be further discussed in the next section.

VI. Discussion

Theoretical Implications

Consumers are using AISA for a variety of reasons including as means to help fulfil their emotional needs which promote general life satisfaction. We develop and test a theoretical model integrating PSR construct into the AISA enabled service context. Our results show that an inanimate entity such as AISA can induce PSR for consumers, which in turn can positively affect consumers' subjective well-being. This is in general in consistent with past studies which have linked human service attributes to subjective well-being.[34,35] In addition, this study extends our understanding of how AISA-enabled service can contribute to subjective well-being.[1] We also advance the PSR theory by establishing how AISA anthropomorphism can be a more important antecedent to PSR as compared to enjoyment.

Our study is a direct response to the call for further research of how AI-enabled services impact consumers.[7,24] To the best of our knowledge, this is the first study to empirically examine how AISA affects subjective well-being. More specifically we identify PSR as a mechanism through which subjective well-being can be enhanced with AISA. PSR conjured from interacting with AISA, a form of automated social presence,[22] results in social support which is critical to subjective well-being. While studies in human– computer Interaction (HCI) and human–robot Interaction (HRI) provided preliminary evidence for social support by social robots[118,119] and that companion robots tend to have positive psychological effects (i.e. decreased feelings of loneliness) by forging social relationships,[120] the mechanism through which they influence well-being is under researched. Additionally, we extend the work of Hartmann[(121)] pertaining PSR. Specifically, Hartmann[(121)] provides strong theoretical arguments that PSR contributes to well-being. By contrast, in our study we find empirical evidence to support this link empirically in the context of AISA, and also identify some conditions, including PSR antecedents and moderators and can affect the relationship.

Overall, these findings contribute to both the literature in the area of service and well-being,[76] and the IS literature in the context of investigating new consumer outcomes.[122]

Another interesting finding of our study was the greater influence of PSR on subjective well-being for male consumers. This result is in contrast to our hypothesis and extant technology-usage studies in which males were found to be less emotionally oriented than females.[60,123] A possible explanation for this finding is based on how AISA differs from other non-AI-based service applications. The user interface of AISA primarily designed for hedonic tasks tend to lean towards being more female-like,[124] thus amplifying the effects of the emotional bonds male users can form with their AISA in satisfying their hedonic needs.[20] This is also in line with prior findings that males hold more positive views towards AISA than females.[19] Indeed, there is evidence to suggest that females may experience higher inhibitions in using new technology due to a perceived lack of control and uncertainty over the technology.[125] These negative dispositions may reduce their overall affective state from engaging with AISA.

Another possible explanation of the result could be related to the motives for using virtual assistants. Extant research looking at implications of gender differences on ICT use has found that males tend to see technology as instrumental to achieving specific outcomes such as entertainment and to obtain information. By contrast females view ICT as instrumental for achieving communication outcomes, e.g., to facilitate maintaining and nurturing relationships.[126-129] This could explain our findings. That is, male users find that virtual assistants improve their well-being by way of helping them accomplish entertainment and information outcomes. By contrast, virtual assistants were not, at present stage of development, found by female participant to improve their well-being to the same degree as the male counterparts to achieve their motives, i.e., to facilitate communication to maintain and nurture relationships.

Overall, our theoretical results underscore the important role of affective attributes in the development of AISA and contribute to the areas of emotion research and consumer well-being in service environments provisioned by AISA.

Managerial Implications

With the knowledge that AISA usage can increase levels of PSR which in turn can increase subjective well-being, consumers can take advantage of AISA services. Accordingly, companies can also take consideration of this finding in the development and implementation of AISA to the market. As our research has highlighted the key role of anthropomorphism as a strong PSR trigger, consumers can now actively seek AISA with more anthropomorphic attributes (e.g. interfaces associated humanlike voice and gestures) which can better cater to a consumer’s specific service situation and thereby fostering more affective interactions.

Second, on the positive link between PSR and subjective well-being, consumers can use AISA as a viable means of meeting their hedonic needs. As such, companies can be more forthcoming on the positive benefits that AISA can bring to consumers' well-being by promoting these as part of the core service benefits in their promotion campaigns.

Finally, consumers can express their interest to companies to be able to personalize their AISA based on specific gender cues such as the AISA name, appearance and tone of voice. Companies with expertise to understand different gender preferences associated with AISA can develop a more effective AISA range to serve a broader and more inclusive market.[124] In addition, consumers can also seek AISA which are able to grow with them for the long term in order to reap the benefits associated with an increase in their well-being. This also lends well to companies seeking to foster greater customer loyalty.

VII. Limitations and Further Research

There are several limitations in our study which represent opportunities for future research. First, our sample was based on US consumers. As such, their perceptions may not be representative of other populations from regions where attitudes and experiences with AI may differ.[130,131] Thus, future research can investigate cultural differences of our model by comparing it based on samples from different countries/regions or sub-cultural groups.

Second, our findings suggest that the length of AISA usage is a moderator of the PSR-subjective well-being link. However, the effects in our study are based on a cross-sectional view. Thus, a better understanding of the shifts in the levels of anthropomorphism, enjoyment, PSR and well-being in the long run through longitudinal studies is worth further investigation.

Third, our interdisciplinary study focused on the role of users as consumers in the service context. Further research with deeper insights from psychology can illuminate how the relationships in our theoretical model may differ for different users with varying psychological characteristics.

Fourth, our focus on this study can been on the moderating effect of the gender of AISA users on the relationship between PSR and subjective well-being. Further research could look at the implications of the effects of assigned AISA gender and how that might influence the relationships that we have identified in this study. The work of Greenwood and Long[(132)] which shows that single (relative to partnered) participants maintained a stronger parasocial relationship with opposite gender characters suggests that this could be promising avenue of further research.

Finally, our findings are based on one type of AISA which falls in the category that is of virtual representation and provides hedonic values. Further research should examine how various types of AISA with different representation-value contexts as identified and presented in this paper, such as social robots with high physical representation and hedonic value, can affect the relationships between anthropomorphism, enjoyment, PSR and subjective well-being. The answer to these questions will become increasingly important as AISA become more sophisticated and permeate more aspects of society.

References

1. Noor N, Rao Hill S, Troshani I. Recasting Service Quality for AI-Based Service. Australasian Marketing Journal. 2021. DOI: 10.1177/18393349211005056.
2. Brill TM, Munoz L, Miller RJ. Siri, Alexa, and other digital assistants: A study of customer satisfaction with artificial intelligence applications. Journal of Marketing Management. 2019;35(15-16):1401-36. DOI: 10.1080/0267257X.2019.1687571.
3. Lee KM, Park N, Song H. Can a robot be perceived as a developing creature? Effects of a robot's long-term cognitive developments on its social presence and people's social responses toward it. Human Communication Research. [Review]. 2005;31(4):538-63. DOI: 10.1111/j.1468-2958.2005.tb00882.x. Cited in: Scopus.
4. De Keyser A, Köcher S, Alkire L, Verbeeck C, Kandampully J. Frontline Service Technology infusion: conceptual archetypes and future research directions. Journal of Service Management. 2019;30(1):156-83. DOI: 10.1108/JOSM-03-2018-0082.
5. Huang M-H, Rust RT. Engaged to a Robot? The Role of AI in Service. Journal of Service Research. 2020;24(1):30-41. DOI: 10.1177/1094670520902266.
6. Wirtz J, Patterson PG, Kunz WH, Gruber T, Lu VN, Paluch S, et al. Brave new world: service robots in the frontline. Journal of Service Management. 2018;29(5):907-31. DOI: 10.1108/JOSM-04-2018-0119.
7. Davenport T, Guha A, Grewal D, Bressgott T. How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science. 2020;48(1):24-42. DOI: 10.1007/s11747-019-00696-0.
8. Rust RT. The future of marketing. International Journal of Research in Marketing. 2019;37(1):15-26. DOI: 10.1016/j.ijresmar.2019.08.002.
9. Huang M-H, Rust RT. Artificial intelligence in service. Journal of Service Research. 2018;21(2):155-72.
10. Huang M-H, Rust RT. A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science. 2021;49:30-50. DOI: 10.1007/s11747-020-00749-9.
11. Shankar V. How artificial intelligence (AI) is reshaping retailing. Journal of Retailing. 2018;94(4):vi-xi. DOI: 10.1016/S0022-4359(18)30076-9.
12. Mordor Intelligence M. Social robot market - Growth, trends and forecasts (2020-2025). Mordor Intelligence; 2020 [cited 2020 22 October]. Available from: https://www.mordorintelligence.com/industry-reports/social-robots-market
13. Adroit Market Research A. 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. GlobeNewswire; 2020 [cited 2020 26 February]. Available from: https://www.globenewswire.com/news-release/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
14. Bock DE, Wolter JS, Ferrell O. Artificial intelligence: disrupting what we know about services. Journal of Services Marketing. 2020;34(3):317-34. DOI: 10.1108/JSM-01-2019-0047.
15. Pantano E, Pizzi G. Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. Journal of Retailing and Consumer Services. 2020;55(102096):1-9. DOI: 10.1016/j.jretconser.2020.102096.

16. Meyer P, Jonas JM, Roth A. Frontline employees' acceptance of and resistance to service robots in stationary retail - an exploratory interview study. SMR - Journal of Service Management Research. 2020;4(1):21-34. DOI: 10.15358/2511-8676-2020-1-21.
17. Meyer-Waarden L, Pavone G, Poocharoentou T, Prayatsup P, Ratinaud M, Tison A, et al. How service quality influences customer acceptance and usage of chatbots? SMR - Journal of Service Management Research. 2020;4(1):35-51. DOI: 10.15358/2511-8676-2020-1-35.
18. Cane S, McCarthy R. Analyzing the factors that affect information systems use: a task-technology fit meta-analysis. Journal of Computer Information Systems. 2009;50(1):108-23. DOI: 10.1080/08874417.2009.11645368.
19. Konok V, Korcsok B, Miklósi Á, Gácsi M. Should we love robots?–The most liked qualities of companion dogs and how they can be implemented in social robots. Computers in Human Behavior. 2018;80:132-42. DOI: 10.1016/j.chb.2017.11.002.
20. Pesce NL. A quarter of us want to have sex with Alexa. MarketWatch; 2017 [cited 2020 28 June]. Available from: https://www.marketwatch.com/story/a-quarter-of-us-want-to-have-sex-with-alexa-2017-04-06-148821
21. Peeters A, Haselager P. Designing virtuous sex robots. International Journal of Social Robotics. 2021;13:55-66. DOI: 10.1007/s12369-019-00592-1.
22. Van Doorn J, Mende M, Noble SM, Hulland J, Ostrom AL, Grewal D, et al. Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. Journal of Service Research. 2017;20(1):43-58.
23. Kiron D, Unruh G. Even if AI can cure loneliness - should it? MIT Sloan Management Review. 2019;60(2):1-4. Cited in: eLibrary; ProQuest One Academic.
24. Lu V, Wirtz J, Kunz W, Paluch S, Gruber T, Martins A, et al. 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. 2020;30(3):361-91. DOI: 10.1108/JSTP-04-2019-0088.
25. Horton D, Wohl RR. Mass communication and para-social interaction: Observations on intimacy at a distance. Psychiatry. 1956;19(3):215-29. DOI: 10.1080/00332747.1956.11023049.
26. Horton D, Strauss A. Interaction in Audience-Participation Shows. American Journal of Sociology. 1957;62(6):579-87. DOI: 10.1086/222106.
27. Han S, Yang H. Understanding adoption of intelligent personal assistants: A parasocial relationship perspective. Industrial Management & Data Systems. 2018;118(3):618-36. DOI: doi:10.1108/IMDS-05-2017-0214.
28. Cronin Jr JJ, Brady MK, Hult GTM. Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. Journal of Retailing. 2000;76(2):193-218. DOI: 10.1016/S0022-4359(00)00028-2.
29. Rubin RB, McHugh MP. Development of parasocial interaction relationships. Journal of Broadcasting and Electronic Media. [Conference Paper]. 1987;31(3):279-92. DOI: 10.1080/08838158709386664. Cited in: Scopus.
30. Henkel AP, Čaić M, Blaurock M, Okan M. Robotic transformative service research: deploying social robots for consumer well-being during Covid-19 and beyond. Journal of Service Management. 2020;31(6):1131-48. DOI: 10.1108/JOSM-05-2020-0145.
31. Zeithaml VA, Berry LL, Parasuraman A. The behavioral consequences of service quality. Journal of Marketing. 1996;60(2):31-46. DOI: 10.1177/002224299606000203.
32. Lim JS, Choe M-j, Zhang J, Noh G-Y. The role of wishful identification, emotional engagement, and parasocial relationships in repeated viewing of live-streaming games:

A social cognitive theory perspective. Computers in Human Behavior. 2020;108(106327):1-10. DOI: 10.1016/j.chb.2020.106327
33. Troebs C-C, Wagner T, Heidemann F. Transformative retail services: Elevating loyalty through customer well-being. Journal of Retailing and Consumer Services. 2018;45:198-206. DOI: 10.1016/j.jretconser.2018.09.009.
34. Su L, Huang S, Chen X. Effects of service fairness and service quality on tourists' behavioral intentions and subjective well-being. Journal of Travel & Tourism Marketing. 2015;32(3):290-307. DOI: 10.1080/10548408.2014.896766.
35. Su L, Swanson SR, Chen X. The effects of perceived service quality on repurchase intentions and subjective well-being of Chinese tourists: The mediating role of relationship quality. Tourism Management. 2016;52:82-95.
36. Xu Y, Shieh C-H, van Esch P, Ling I-L. AI customer service: Task complexity, problem-solving ability, and usage intention. Australasian Marketing Journal (AMJ). 2020;28(4):189-99. DOI: 10.1016/j.ausmj.2020.03.005.
37. Van Der Heijden H. User Acceptance of Hedonic Information Systems. MIS Quarterly. 2004;28(4):695-704. DOI: 10.2307/25148660.
38. Sillice MA, Morokoff PJ, Ferszt G, Bickmore T, Bock BC, Lantini R, et al. Using relational agents to promote exercise and sun protection: Assessment of participants' experiences with two interventions. Journal of Medical Internet research. 2018;20(2):e48. DOI: 10.2196/jmir.7640.
39. Wolters MK, Kelly F, Kilgour J. Designing a spoken dialogue interface to an intelligent cognitive assistant for people with dementia. Health Informatics Journal. 2016;22(4):854-66. DOI: 10.1177/1460458215593329.
40. Pandey AK, Gelin R. A mass-produced sociable humanoid robot: pepper: the first machine of its kind. IEEE Robotics & Automation Magazine. 2018;25(3):40-8. DOI: 10.1109/MRA.2018.2833157.
41. Coghlan S, Vetere F, Waycott J, Neves BB. Could social robots make us kinder or crueller to humans and animals? International Journal of Social Robotics. 2019(11):741-51. DOI: 10.1007/s12369-019-00583-2.
42. Ta V, Griffith C, Boatfield C, Wang X, Civitello M, Bader H, et al. User experiences of social support from companion chatbots in everyday contexts: Thematic analysis. Journal of Medical Internet Research. 2020;22(3):e16235. DOI: 10.2196/16235.
43. Ewers K, Baier D, Höhn N. Siri, do I like you? Digital voice assistants and their acceptance by consumers. SMR - Journal of Service Management Research. 2020;4(1):52-66. DOI: 10.15358/2511-8676-2020-1-52.
44. Hoy MB. Alexa, Siri, Cortana, and More: An introduction to Voice Assistants. Medical Reference Services Quarterly. 2018;37(1):81-8. DOI: 10.1080/02763869.2018.1404391.
45. Rubin AM, Perse EM, Powell RA. Loneliness, parasocial interaction, and local television news viewing. Human Communication Research. 1985;12(2):155-80. DOI: 10.1111/j.1468-2958.1985.tb00071.x.
46. Dibble JL, Hartmann T, Rosaen SF. Parasocial interaction and parasocial relationship: Conceptual clarification and a critical assessment of measures. Human Communication Research. 2016;42(1):21-44. DOI: 10.1111/hcre.12063.
47. Rosaen SF, Dibble JL. Clarifying the role of attachment and social compensation on parasocial relationships with television characters. Communication Studies. 2016;67(2):147-62. DOI: 10.1080/10510974.2015.1121898.
48. Hartmann T. Parasocial interactions and paracommunication with new media characters: Routledge; 2008.

49. Hartmann T, Stuke D, Daschmann G. Positive parasocial relationships with drivers Affect suspense in racing sport spectators. Journal of Media Psychology: Theories, Methods, and Applications. 2008;20(1):24-34. DOI: 10.1027/1864-1105.20.1.24.
50. Tsiotsou RH. The role of social and parasocial relationships on social networking sites loyalty. Computers in Human Behavior. 2015;48:401-14. DOI: 10.1016/j.chb.2015.01.064.
51. Zheng X, Men J, Xiang L, Yang F. Role of technology attraction and parasocial interaction in social shopping websites. International Journal of Information Management. [Article]. 2020;51(102043):1-13. DOI: 10.1016/j.ijinfomgt.2019.102043. Cited in: Scopus.
52. Lu L, Cai R, Gursoy D. Developing and validating a service robot integration willingness scale. International Journal of Hospitality Management. 2019;80:36-51. DOI: 10.1016/j.ijhm.2019.01.005.
53. Gursoy D, Chi OH, Lu L, Nunkoo R. Consumers acceptance of artificially intelligent (AI) device use in service delivery. International Journal of Information Management. 2019;49:157-69. DOI: 10.1016/j.ijinfomgt.2019.03.008.
54. Song SY. Modeling the consumer acceptance of retail service robots 2017.
55. Niemelä M, Arvola A, Aaltonen I. Monitoring the acceptance of a social service robot in a shopping mall: first results. In: Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-robot Interaction. 2017 p. 225-6.
56. Troshani I, Rao Hill S, Sherman C, Arthur D. Do We Trust in AI? Role of Anthropomorphism and Intelligence. Journal of Computer Information Systems. 2020:1-11. DOI: 10.1080/08874417.2020.1788473.
57. Kepuska V, Bohouta G. Next-generation of virtual personal assistants (microsoft cortana, apple siri, amazon alexa and google home). In: 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC). 2018: IEEE; p. 99-103.
58. Qiu L, Benbasat I. Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. Journal of Management Information Systems. 2009;25(4):145-81. DOI: 10.2753/MIS0742-1222250405.
59. Fetscherin M. What type of relationship do we have with loved brands? Journal of Consumer Marketing. 2014;31(6/7):430-40. DOI: 10.1108/JCM-05-2014-0969.
60. Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Quarterly. 2012;36(1):157-78. DOI: 10.2307/41410412
61. Allam H, Bliemel M, Spiteri L, Blustein J, Ali-Hassan H. Applying a multi-dimensional hedonic concept of intrinsic motivation on social tagging tools: A theoretical model and empirical validation. International Journal of Information Management. 2019;45:211-22. DOI: 10.1016/j.ijinfomgt.2018.11.005.
62. Aldossari MQ, Sidorova A. Consumer acceptance of Internet of Things (IoT): Smart home context. Journal of Computer Information Systems. 2020;60(6):507-17. DOI: 10.1080/08874417.2018.1543000.
63. Suki NM, Suki NM. Exploring the relationship between perceived usefulness, perceived ease of use, perceived enjoyment, attitude and subscribers' intention towards using 3G mobile services. Journal of Information Technology Management. 2011;22(1):1-7.
64. Teo T, Noyes J. An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation

modeling approach. Computers & Education. 2011;57(2):1645-53. DOI: 10.1016/j.compedu.2011.03.002.

65. Hamari J. Why do people buy virtual goods? Attitude toward virtual good purchases versus game enjoyment. International Journal of Information Management. 2015;35:299-308. DOI: 10.1016/j.ijinfomgt.2015.01.007.
66. Ramayah T, Ignatius J. Impact of perceived usefulness, perceived ease of use and perceived enjoyment on intention to shop online. ICFAI Journal of Systems Management (IJSM). 2005;3(3):36-51.
67. Fryer LK, Ainley M, Thompson A, Gibson A, Sherlock Z. Stimulating and sustaining interest in a language course: An experimental comparison of Chatbot and Human task partners. Computers in Human Behavior. 2017;75:461-8. DOI: 10.1016/j.chb.2017.05.045.
68. Giles DC. Parasocial interaction: A review of the literature and a model for future research. Media Psychology. [Review]. 2002;4:279-305. DOI: 10.1207/S1532785XMEP0403_04. Cited in: Scopus.
69. Diener E. Subjective well-being. Psychological Bulletin. 1984;95(3):542-75. DOI: 10.1037/0033-2909.95.3.542.
70. Anderson L, Ostrom AL, Corus C, Fisk RP, Gallan AS, Giraldo M, et al. Transformative service research: An agenda for the future. Journal of Business Research. 2013;66(8):1203-10. DOI: 10.1016/j.jbusres.2012.08.013.
71. Diener E, Emmons RA, Larsen RJ, Griffin S. The satisfaction with life scale. Journal of Personality Assessment. 1985;49(1):71-5. DOI: 10.1207/s15327752jpa4901_13.
72. Diener E, Suh EM, Lucas RE, Smith HL. Subjective well-being: Three decades of progress. Psychological Bulletin. 1999;125(2):276-302.
73. Larsen RJ, Diener E, Emmons RA. An evaluation of subjective well-being measures. Social indicators research. 1985;17(1):1-17. DOI: 10.1007/BF00354108.
74. Pavot W, Diener E. The affective and cognitive context of self-reported measures of subjective well-being. Social Indicators Research. 1993;28(1):1-20. DOI: 10.1007/BF01086714.
75. Lyubomirsky S, Lepper HS. A measure of subjective happiness: Preliminary reliability and construct validation. Social Indicators Research. 1999;46(2):137-55. DOI: 10.1023/A:1006824100041.
76. Anderson L, Ostrom AL. Transformative service research: advancing our knowledge about service and well-being. Journal of Service Research. 2015;18(3):243-9. DOI: 10.1177/1094670515591316.
77. Ostrom AL, Parasuraman A, Bowen DE, Patricio L, Voss CA. Service research priorities in a rapidly changing context. Journal of Service Research. 2015;18(2):127-59. DOI: 10.1177/1094670515576315.
78. Rafaeli A, Altman D, Gremler DD, Huang M-H, Grewal D, Iyer B, et al. The future of frontline research: invited commentaries. Journal of Service Research. 2017;20(1):91-9. DOI: 10.1177/1094670516679275.
79. Rosenbaum MS. Transformative service research: focus on well-being. The Service Industries Journal. 2015;35(7-8):363-7. DOI: 10.1080/02642069.2015.1025061.
80. Parasuraman A. Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. Journal of Service Research. 2000;2(4):307-20. DOI: 10.1177/109467050024001.
81. Venkatesh V, Bala H. Technology acceptance model 3 and a research agenda on interventions. Decision Sciences. 2008;39(2):273-315. DOI: 10.1111/j.1540-5915.2008.00192.x.

82. Chiu C-M, Cheng H-L, Huang H-Y, Chen C-F. Exploring individuals' subjective well-being and loyalty towards social network sites from the perspective of network externalities: The Facebook case. International Journal of Information Management. 2013;33(3):539-52. DOI: 10.1016/j.ijinfomgt.2013.01.007.
83. Cohen S. Social relationships and health. American Psychologist. 2004;59(8):676-84.
84. Gefen D, Straub DW. Gender differences in the perception and use of e-mail: An extension to the technology acceptance model. MIS Quarterly. 1997:389-400. DOI: 10.2307/249720.
85. Ramkissoon H, Nunkoo R. More than just biological sex differences: Examining the structural relationship between gender identity and information search behavior. Journal of Hospitality & Tourism Research. 2012;36(2):191-215. DOI: 10.1177/1096348010388662.
86. Kamide H, Kawabe K, Shigemi S, Arai T. Development of a psychological scale for general impressions of humanoid. Advanced Robotics. 2013;27(1):3-17. DOI: 10.1080/01691864.2013.751159.
87. Schiappa E, Allen M, Gregg PB. Parasocial relationships and television: A meta-analysis of the effects: Routledge; 2007.
88. Hu M. The influence of a scandal on parasocial relationship, parasocial interaction, and parasocial breakup. Psychology of Popular Media Culture. 2016;5(3):217-31. DOI: 10.1037/ppm0000068.
89. Lin J-SC, Hsieh P-L. Assessing the self-service technology encounters: development and validation of SSTQUAL scale. Journal of retailing. 2011;87(2):194-206.
90. Orel FD, Kara A. Supermarket self-checkout service quality, customer satisfaction, and loyalty: Empirical evidence from an emerging market. Journal of Retailing and Consumer Services. 2014;21(2):118-29. DOI: 10.1016/j.jretconser.2013.07.002.
91. Considine E, Cormican K. Self-service technology adoption: an analysis of customer to technology interactions. Procedia Computer Science. 2016;100:103-9.
92. Moussawi S, Koufaris M. 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 p. 115-24. Available from: https://hdl.handle.net/10125/59452
93. Bartneck C, Kulić D, Croft E, Zoghbi S. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. International Journal of Social Robotics. 2009;1(1):71-81. DOI: 10.1007/s12369-008-0001-3.
94. Weiss A, Bartneck C. Meta analysis of the usage of the godspeed questionnaire series. In: 2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN). 2015: IEEE; p. 381-8.
95. Whang C, Im H. " I Like Your Suggestion!" the role of humanlikeness and parasocial relationship on the website versus voice shopper's perception of recommendations. Psychology & Marketing. 2020.
96. Netemeyer RG, Bearden WO, Sharma S. Scaling procedures: Issues and applications: Sage Publications; 2003.
97. Dabholkar PA. Consumer evaluations of new technology-based self-service options: an investigation of alternative models of service quality. International Journal of Research in Marketing. 1996;13(1):29-51. DOI: 10.1016/0167-8116(95)00027-5.
98. Liu F, Xiao B, Lim ET, Tan C-W. The art of appeal in electronic commerce: understanding the impact of product and website quality on online purchases. Internet Research. 2017;27(4):752-71. DOI: 10.1108/IntR-09-2016-0280.

99. Basak E, Calisir F. An empirical study on factors affecting continuance intention of using Facebook. Computers in Human Behavior. 2015;48:181-9. DOI: 10.1016/j.chb.2015.01.055.
100. Vimalkumar M, Sharma SK, Singh JB, Dwivedi YK. 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. Computers in Human Behavior. 2021;120(106763). DOI: 10.1016/j.chb.2021.106763.
101. PwC. Artificial intelligence: Touchpoints with consumers. 2018. Available from: https://www.pwc.at/de/publikationen/branchen-und-wirtschaftsstudien/ai_intelligence_2018.pdf
102. Oppenheimer DM, Meyvis T, Davidenko N. Instructional manipulation checks: Detecting satisficing to increase statistical power. Journal of Experimental Social Psychology. 2009;45(4):867-72. DOI: 10.1016/j.jesp.2009.03.009.
103. MacKenzie SB, Podsakoff PM. Common method bias in marketing: Causes, mechanisms, and procedural remedies. Journal of Retailing. 2012;88(4):542-55. DOI: 10.1016/j.jretai.2012.08.001.
104. Herzog AR, Bachman JG. Effects of questionnaire length on response quality. Public Opinion Quarterly. 1981;45(4):549-59. DOI: 10.1086/268687.
105. Olson C, Kemery K. Voice report. 2019. Available from: https://advertiseonbing-blob.azureedge.net/blob/bingads/media/insight/whitepapers/2019/04%20apr/voice-report/bingads_2019_voicereport.pdf
106. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. European Business Review. 2019;31(1):2-24. DOI: 10.1108/EBR-11-2018-0203.
107. Sarstedt M, Hair Jr JF, Nitzl C, Ringle CM, Howard MC. Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses! International Journal of Market Research. 2020;62(3):288-99. DOI: 10.1177/1470785320915686.
108. Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis. Eighth ed. United Kingdom: Cengage Learning EMEA; 2019.
109. Benitez J, Henseler J, Castillo A, Schuberth F. How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. Information & Management. 2020;57(2):103168. DOI: 10.1016/j.im.2019.05.003.
110. Hair JF, Sarstedt M, Ringle CM. Rethinking some of the rethinking of partial least squares. European Journal of Marketing. 2019;53(4):566-84. DOI: 10.1108/EJM-10-2018-0665.
111. Fernandes T, Oliveira E. Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. Journal of Business Research. 2021;122:180-91. DOI: 10.1016/j.jbusres.2020.08.058.
112. Henseler J, Hubona G, Ray PA. Using PLS path modeling in new technology research: updated guidelines. Industrial management & data systems. 2016;116(1):2-20. DOI: 10.1108/IMDS-09-2015-0382.
113. Bagozzi RP, Yi Y. Specification, evaluation, and interpretation of structural equation models. Journal of the Academy of Marketing Science. 2012;40(1):8-34. DOI: 10.1007/s11747-011-0278-x.
114. Bagozzi RP, Yi Y. On the evaluation of structural equation models. Journal of the Academy of Marketing Science. 1988;16(1):74-94. DOI: 10.1007/BF02723327.
115. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science. 2015;43(1):115-35. DOI: 10.1007/s11747-014-0403-8.

116. Fuller CM, Simmering MJ, Atinc G, Atinc Y, Babin BJ. Common methods variance detection in business research. Journal of Business Research. 2016;69(8):3192-8. DOI: 10.1016/j.jbusres.2015.12.008.
117. Kock N. Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration. 2015;11(4):1-10.
118. De Graaf MM, Allouch SB. Exploring influencing variables for the acceptance of social robots. Robotics and Autonomous Systems. 2013;61(12):1476-86. DOI: 10.1016/j.robot.2013.07.007.
119. Sundar SS, Jung EH, Waddell TF, Kim KJ. Cheery companions or serious assistants? Role and demeanor congruity as predictors of robot attraction and use intentions among senior citizens. International Journal of Human-Computer Studies. 2017;97:88-97. DOI: 10.1016/j.ijhcs.2016.08.006.
120. Robinson H, MacDonald B, Broadbent E. The role of healthcare robots for older people at home: A review. International Journal of Social Robotics. 2014;6(4):575-91. DOI: 10.1007/s12369-014-0242-2.
121. Hartmann T. Parasocial interaction, parasocial relationships, and well-being. The Routledge handbook of media use and well-being: International perspectives on theory and research on positive media effects. 2016:131-44.
122. Venkatesh V, Thong JYL, Xu X. Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. Journal of the Association for Information Systems. 2016;17(5):328-76.
123. Shi S, Chen Y, Chow WS. Key values driving continued interaction on brand pages in social media: An examination across genders. Computers in Human Behavior. 2016;62:578-89. DOI: 10.1016/j.chb.2016.04.017.
124. Fung P. This is why AI has a gender problem. World Economic Forum; 2019 [cited 2020 27 October]. Available from: https://www.weforum.org/agenda/2019/06/this-is-why-ai-has-a-gender-problem
125. Rojas-Méndez JI, Parasuraman A, Papadopoulos N. Demographics, attitudes, and technology readiness: A cross-cultural analysis and model validation. Marketing Intelligence & Planning. 2017;35(1):18-39. DOI: 10.1108/MIP-08-2015-0163.
126. Roberts J, Yaya L, Manolis C. The invisible addiction: Cell-phone activities and addiction among male and female college students. Journal of Behavioral Addictions. 2014;3(4):254-65. DOI: 10.1556/jba.3.2014.015.
127. Junco R, Merson D, Salter DW. The effect of gender, ethnicity, and income on college students' use of communication technologies. Cyberpsychology, Behavior, and Social Networking. 2010;13(6):619-27. DOI: 10.1089/cyber.2009.0357.
128. Junco R, Cole-Avent GA. An introduction to technologies commonly used by college students. New Directions for Student Services. 2008;2008(124):3-17. DOI: 10.1002/ss.292.
129. Geser H. Are girls (even) more addicted? Some gender patterns of cell phone usage.: Sociology in Switzerland: Sociology of the Mobile Phone; 2006 [cited 2021 24 May]. Available from: https://socio.ch/mobile/t_geser3.pdf
130. MacDorman KF, Vasudevan SK, Ho C-C. Does Japan really have robot mania? Comparing attitudes by implicit and explicit measures. AI & society. 2009;23:485-510. DOI: 10.1007/s00146-008-0181-2.
131. Funk C, Tyson A, Kennedy B, Johnson C. 4. Publics express a mix of views on AI, childhood vaccines, food and space issues. Pew Research Center; 2020 [cited 2021 13 January]. Available from: https://www.pewresearch.org/science/2020/09/29/publics-express-a-mix-of-views-on-ai-childhood-vaccines-food-and-space-issues/

132. Greenwood DN, Long CR. Attachment, belongingness needs, and relationship status predict imagined intimacy with media figures. Communication Research. 2011;38(2):278-97. DOI: 10.1177/0093650210362687.
133. Jones JL. Robots at the tipping point: The road to iRobot Roomba. IEEE Robotics and Automation Magazine. 2006;13(1):76-8. DOI: 10.1109/MRA.2006.1598056.
134. Endsley MR. Autonomous driving systems: A preliminary naturalistic study of the Tesla Model S. Journal of Cognitive Engineering and Decision Making. 2017;11(3):225-38. DOI: 10.1177/1555343417695197.
135. Grammarly. How we use AI to enhance your writing. Grammarly; 2018 [cited 2020 16 May]. Available from: https://www.grammarly.com/blog/how-grammarly-uses-ai

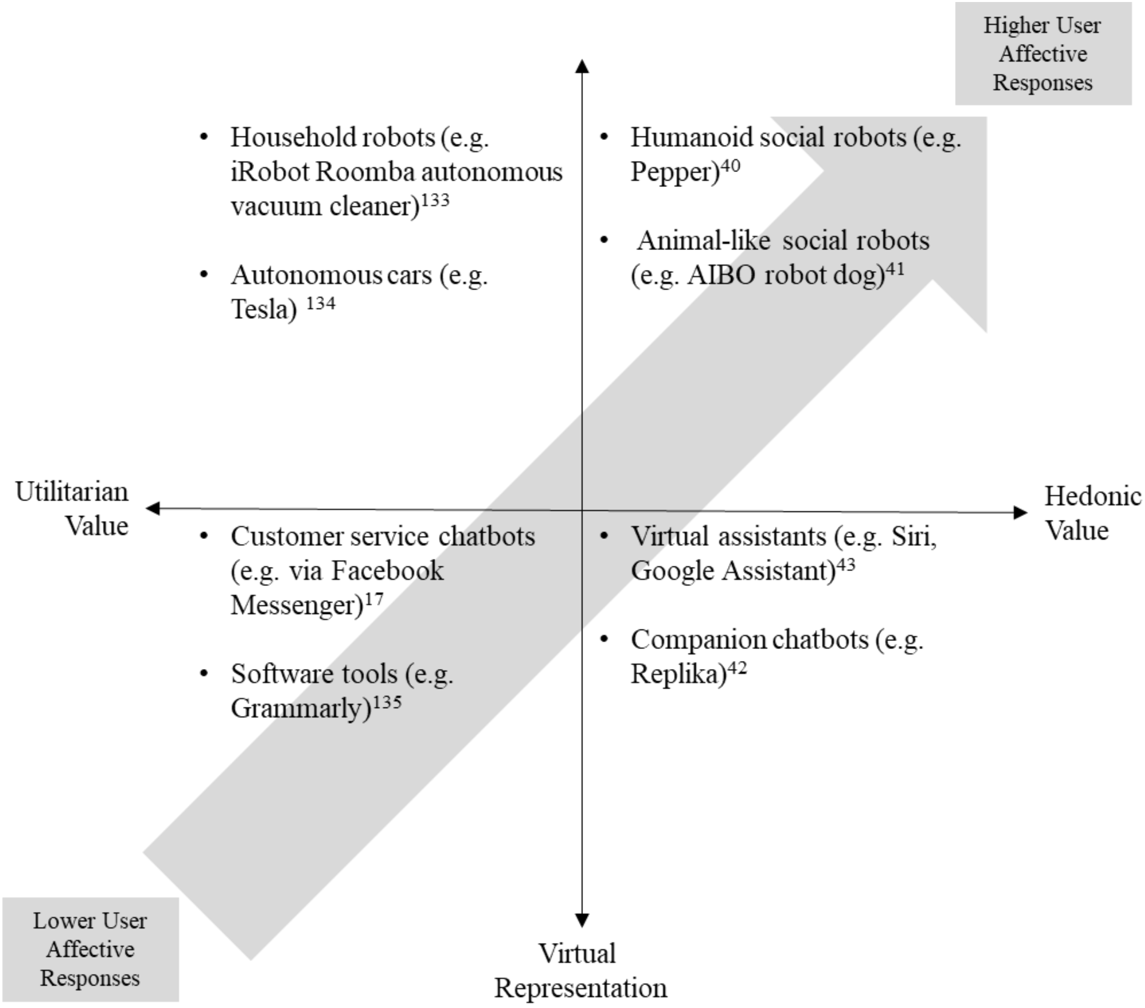

Figure 1. Spectrum of AISA by general representation, value to consumers and affective responses.

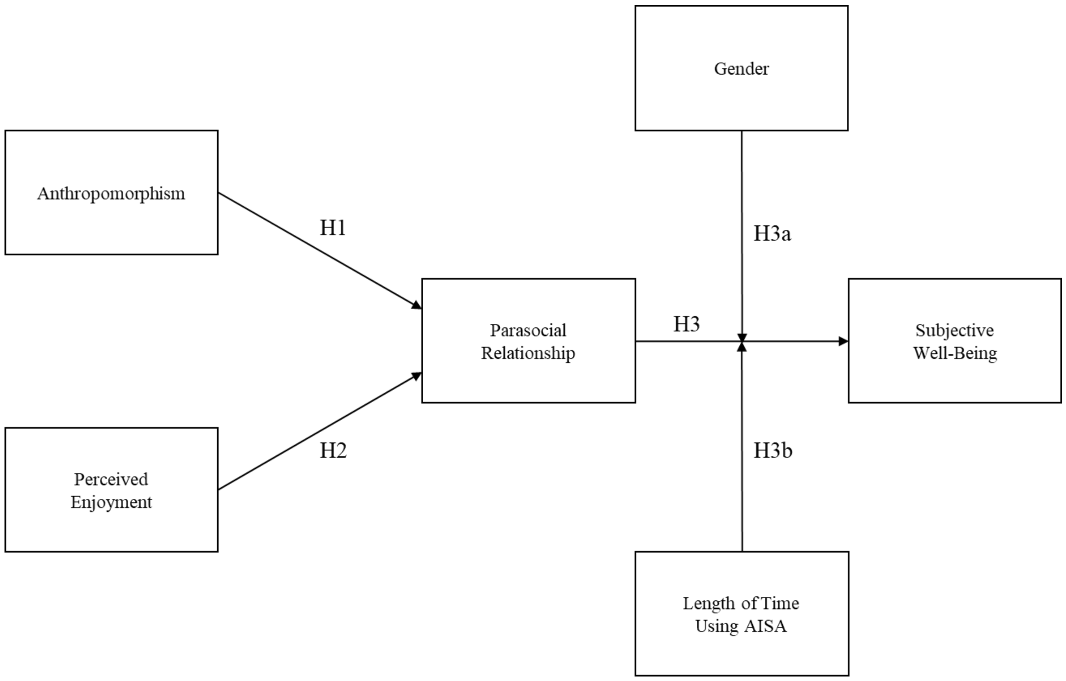

Figure 2. Research model.

Table 1. Survey items.

Construct	Item		Source
Anthropomorphism	ANT1	The AISA has humanlike features.	Moussawi and Koufaris,(92) Bartneck et al.(93)
	ANT2	The AISA has personality.	
	ANT3	The AISA is able to behave like a human.	
	ANT4	The AISA is able to communicate like a human.	
Enjoyment	ENJ1	Using the AISA is fun.	Dabholkar (97)
	ENJ2	Using the AISA is enjoyable.	
	ENJ3	Using the AISA is interesting.	
	ENJ4	Using the AISA is entertaining.	
Parasocial relationship	PSR1	I think the AISA is like an old friend.	Hartmann et al.(49)
	PSR2	The AISA makes me feel as comfortable as when I am with friends.	
	PSR3	I think about the AISA even when I am not interacting with it.	
	PSR4	I miss the AISA if I do not use it for a long time.	
	PSR5	I feel that I know the AISA very well.	
Subjective well-being	SWB1	In general, I consider myself a very happy person.	Su et al.(35)
	SWB2	Compared to most of my peers, I consider myself happier.	
	SWB3	I am generally very happy and enjoy life.	

Table 2. Profile of survey respondents.

Category	Frequency	Percentage	Category	Frequency	Percentage
			Work industry		
Gender			Accommodation and food services	18	4.4
Male	203	49.8			
Female	205	50.2	Administrative and support services	16	3.9
Total	408	100.0			
			Arts and recreation services	10	2.5
Age					
18-24	67	16.4	Construction	8	2.0
25-34	125	30.6	Education and training	31	7.6
35-44	114	27.9	Electricity, gas, water and waste services	9	2.2
45-54	46	11.3			
55-64	30	7.4	Financial and insurance services	36	8.8
65 and above	26	6.4			
Total	408	100.0	Health care and social assistance	36	8.8
Highest education			Information media and telecommunications	24	5.9
Less than high school	7	1.7			
High school	76	18.6	Manufacturing	6	1.5
Vocational training	15	3.7	Mining	3	.7
Some college	111	27.2	Professional, scientific and technical services	44	10.8
Bachelor's degree	120	29.4			
Postgraduate degree	79	19.4	Public administration and safety	12	2.9
Total	408	100.0			
			Rental, hiring and real estate services	7	1.7
Personal annual income (USD)					
			Retail trade	39	9.6
Less than $25,000	100	24.5	Transport, postal and warehousing	14	3.4
$25,000 to $49,999	96	23.5			
$50,000 to $74,999	82	20.1	Wholesale Trade	1	.2
$75,000 to $99,999	53	13.0	Other Industries	19	4.7
$100,000 and more	77	18.9	Retired	22	5.4
Total	408	100.0	Unemployed	53	13.0
			Total	408	100.0
AISA usage frequency			*Virtual assistant type*		
Daily	204	50.0	Alexa	131	32.1
Weekly	132	32.4	Bixby	17	4.2
Every 2-3 weeks	31	7.6	Cortana	1	.2
Monthly	21	5.1	Google Assistant	118	28.9
Every 2-3 months	12	2.9	Google Home Mini	30	7.4
Every 4-6 months	2	.5	Google Nest Mini	1	.2
Once a year	6	1.5	Siri	110	27.0
Total	408	100.0	Total	408	100.0
AISA usage experience					
Less than 1 year	92	22.5			
1-3 years	213	52.2			
4-5 years	75	18.4			
6-7 years	22	5.4			
8 years and above	6	1.5			
Total	408	100.0			

Table 3. Reliability and convergent validity results of measurement model.

Construct	Item		Mean	Standard deviation	Loading	Cronbach's alpha	Composite reliability	AVE
Anthropomorphism	ANT1	The AISA has humanlike features.	4.47	1.45	.83	.85	.90	.69
	ANT2	The AISA has personality.	4.84	1.48	.78			
	ANT3	The AISA is able to behave like a human.	4.45	1.52	.88			
	ANT4	The AISA is able to communicate like a human.	4.81	1.42	.84			
Enjoyment	ENJ1	Using the AISA is fun.	5.66	1.25	.87	.90	.93	.76
	ENJ2	Using the AISA is enjoyable.	5.68	1.19	.91			
	ENJ3	Using the AISA is interesting.	5.75	1.07	.87			
	ENJ4	Using the AISA is entertaining.	5.68	1.21	.84			
Parasocial relationship	PSR1	I think the AISA is like an old friend.	3.88	1.80	.86	.89	.92	.70
	PSR2	The AISA makes me feel as comfortable as when I am with friends.	4.23	1.73	.82			
	PSR3	I think about the AISA even when I am not interacting with it.	3.34	1.93	.84			
	PSR4	I miss the AISA if I do not use it for a long time.	3.57	1.92	.86			
	PSR5	I feel that I know the AISA very well.	4.52	1.62	.81			
Subjective well-being	SWB1	In general, I consider myself a very happy person.	5.01	1.51	.92	.89	.93	.81
	SWB2	Compared to most of my peers, I consider myself happier.	4.57	1.56	.90			
	SWB3	I am generally very happy and enjoy life.	5.03	1.51	.89			

Table 4. Discriminant validity results of measurement model using HTMT analysis.

Construct	Anthropomorphism	Enjoyment	Parasocial relationship	Subjective well-being
Anthropomorphism				
Enjoyment	.51			
Parasocial Relationship	.70	.54		
Subjective Well-Being	.26	.25	.35	

Table 5. Hypotheses testing results for main paths in research model.

Hypothesis	β Values	*p* Values	Result
H1: Anthropomorphism → Parasocial Relationship	.50	.001	Supported
H2: Enjoyment → Parasocial Relationship	.26	.001	Supported
H3: Parasocial Relationship → Subjective Well-Being	.31	.001	Supported