

The Smarter, the Better?!

Customer Well-Being, Engagement, and Perceptions in Smart Service Systems

Abstract

Smart service systems – that is, configurations of smart products and service providers that deliver smart services – are striving to increase the smartness of their offering, but potential consequences for customer well-being are largely overlooked. Therefore, this research investigates the impact of smartness on customer well-being (here, self-efficacy and technology anxiety) through (1) customer engagement with different smart service system actors (here, smart products and service providers) and (2) customer perceptions (here, personalization and intrusiveness perceptions) and their associated importance (here, need for personalization and intrusiveness sensitivity). A scenario-based experiment ($n = 730$) – which is preceded by a systematic review to conceptualize smartness – shows that customers perceive more personalization than intrusiveness in case of higher levels of smartness, resulting in customer engagement with the smart product and to some extent with the service provider. Via customer engagement with the smart product, higher levels of smartness stimulate self-efficacy, especially for customers with a high need for personalization. When customers' need for personalization is high and their intrusiveness sensitivity is low, higher levels of smartness also reduce technology anxiety via customer engagement with the smart product. Hence, the conclusion is: “The smarter, the better!”, whereby the relationship between smartness and well-being (here, self-efficacy and technological anxiety) is significantly influenced by customer heterogeneity. These findings help business practitioners in boosting customer well-being by increasing customer engagement through higher levels of smartness of their service system.

Keywords: Smart Service System; Smart Product; Personalization; Intrusiveness; Customer Engagement; Customer Well-Being

1. Introduction

The household penetration of smart products like smart home devices is expected to increase to nearly 2 billion units worldwide by 2023 (Statista, 2020). In this context, companies develop smart services – that is, services enabled by smart products – at an ever-faster pace (Langley et al., 2020; McKinsey & Company, 2017). LG, for instance, evolved from their initial Internet Digital DIOS (i.e., a simple smart refrigerator that can show the items in the fridge by means of a camera and that can connect to the Internet which allows customers to search for recipes or weather forecasts) to their latest InstaView ThinQ fridge (i.e., a smart refrigerator that recognizes the grocery items inside and based on this information suggests recipes and options for reordering items at a connected grocery store). As illustrated by this example, LG continuously increases the smartness of its offerings, by which smartness reflects the extent to which smart services (e.g., keeping inventories and ordering groceries) are enabled through smart products (e.g., smart fridge).

In a world where the smartness of offerings increases at a drastic rate, there is growing attention for customer well-being among researchers (e.g., Anderson et al., 2013; Ostrom, Parasuraman, Bowen, Patrício, & Voss, 2015; Volkmer & Lerner, 2019) and policymakers (e.g., Broadband Commission, 2017; European Commission, 2018; European Commission, 2020). More particularly, they call upon research that stimulates the development of technology-based services – such as smart services – that boost customer well-being (here, self-efficacy and technology anxiety) (e.g., Hollebeek & Belk, 2018). Extant literature suggests that a platform to effectuate well-being implications can be provided by customer engagement with different actors in smart service systems (David, Roberts, & Christenson, 2018; Horwood & Anglim, 2019; Lee, Kwon, Lee, & Kim, 2017). In fact, smart service systems encompass

not only (1) *smart products* through which services are provided (e.g., smart fridge) but also (2) *service providers* whose offerings are enabled by smart products (e.g., grocery store) (Beverungen, Müller, Matzner, Mendling, & Vom Brocke, 2019). Customer engagement reflects thus a psychological state of mind with cognitive, affective, and behavioral dimensions towards both smart products and service providers (Beverungen et al., 2019; Hollebeek, Glynn, & Brodie, 2014; Pansari & Kumar, 2017). While myriad researchers call for studying service systems from a customer engagement and/or well-being perspective (e.g., Hollebeek & Belk, 2018; Alexander, Jaakkola, & Hollebeek, 2017; Zeithaml, Verleye, Hatak, Koller, & Zauner, 2020), the implications of customer engagement with different actors in service systems with higher smartness levels for customer well-being remain unclear.

Against this background, the present research aims to gain insight into the implications of higher levels of smartness for customer well-being through customer engagement with different smart service system actors (here, smart product and service provider), thereby paying specific attention to the underlying mechanisms of these relationships.

Regarding the underlying mechanisms, recent research suggests that higher levels of smartness are often associated with more personalized services (i.e., the extent to which offerings are tailored to customers' specific needs and preferences) (e.g., Kabadayi, Ali, Choi, Joosten, & Lu, 2019; Roy, Balaji, Sadeque, Nguyen, & Melewar, 2017). Meanwhile, popular press raises concerns about the neglect of possible implications for customers' perceived intrusiveness (i.e., the extent to which customers experience interferences in their lives). These concerns are resonated by quotes like 'Norway: Deeply intrusive' COVID-19 contact-tracing app halted' (Amnesty International UK, 2020) and 'Activate This 'Bracelet of Silence,' and Alexa Can't Eavesdrop' (Hill, 2020). Indeed, customers' daily lives are swiftly being infiltrated

by smart service systems (Beverungen et al., 2019; Fischer et al., 2020; Lim & Maglio, 2018), which can give rise to intrusiveness perceptions (Mani & Chouk, 2016; Xu, Luo, Carroll, & Rosson, 2011). To date, research has mainly focused on personalization perceptions of smart service systems as these stimulate customer engagement (e.g., Bleier, De Keyser, & Verleye, 2018; Roy et al., 2017). Meanwhile, potential intrusiveness consequences of smartness received little research attention, even though they might mitigate the positive impact of perceived personalization on customer engagement. Based upon the aforementioned arguments, we propose customer perceptions (here, perceived personalization and perceived intrusiveness) along with their associated importance (here, need for personalization and intrusiveness sensitivity) as exploratory mechanisms for the way in which smartness affects customer well-being through customer engagement.

By investigating the smartness–well-being relationship through customer perceptions and customer engagement, the present research contributes to the literature on smart service systems, customer well-being, and customer engagement in various ways. First, this research contributes to the *smart service system literature* by proposing the level of smartness as a key differentiator in the smart service market and identifying the four essential and inherently linked characteristics that constitute the smartness of service systems (i.e., awareness, connectivity, actuation, and dynamism), thereby consolidating a wide variety of heterogeneous definitions of smartness in the smart service literature in a systematic way. Moreover, by exploring how the level of smartness influences customer well-being (here, self-efficacy and technology anxiety), this inquiry progresses the smart service system literature in which customer well-being is underexplored.

Next, this research contributes to the *customer well-being literature* as it unravels the smartness–well-being relationship by exploring the mediating role of customer engagement. Indeed, studying the engagement–well-being responds to recent calls for research on the relationship between technology-facilitated engagement and customer well-being (Hollebeek & Belk, 2018). More particularly, this inquiry reveals how customer engagement influences customer well-being with its eudaimonic facet (i.e., extent of self-realization; here, self-efficacy) and its hedonic facet (i.e., extent of pleasure; here, technological anxiety). As such, this research provides an extensive understanding of the engagement–well-being relationship and hence advances the literature on customer well-being.

Finally, this research contributes to the *customer engagement literature* by investigating – in line with calls for research on engagement in complex systems (Alexander et al., 2017; Brodie, Fehrer, Jaakkola, & Conduit, 2019; Zeithaml et al., 2020) – how customers engage with different actors in service systems with various levels of smartness. Although smart service systems consist of smart products and service providers with whom customers can engage (Beverungen et al., 2019; Novak & Hoffman, 2018; Schweitzer, Belk, Jordan, & Ortner, 2019), (empirical) insights into the relationship between the level of smartness of service systems and customer engagement with the smart product and service providers are indeed lacking. In response to this gap, the present research explores the mechanisms through which smartness affects customer engagement with different smart service systems actors (here, personalization and intrusiveness perceptions along with their associated importance). As such, this research shows whether higher levels of smartness affect different actors in smart service systems in various ways.

From a managerial perspective, practitioners in smart service systems gain insight into what smartness entails (i.e., smartness characteristics) and how to design their service system in terms of its level of smartness, so that customer engagement and customer well-being are improved.

The subsequent section discusses our conceptual framework and hypotheses. Next, we describe the exploratory study and the main study. We close by discussing the findings, the theoretical and managerial implications, as well as the limitations and future research avenues.

2. Conceptual Framework and Hypotheses

The first section elaborates on the characteristics of smart service systems, thereby proposing smartness as a key differentiator in the smart service market. The subsequent section presents hypotheses about the relationship between smartness and customer engagement with smart service system actors, thereby taking personalization and intrusiveness mechanisms into account. The final section proposes hypotheses about the engagement–well-being relationship.

2.1 Conceptualizing the Smartness of Service Systems

Smart service systems are configurations of smart products and service providers that deliver smart services (Beverungen et al., 2019). Indeed, smart services are services enabled by smart products, which refer to objects that display both physical components (i.e., mechanical and electronic parts) and digital components (i.e., data storage, controls, software, and embedded operating systems) (Anke, 2019; Porter & Heppelmann, 2014). Despite a growing body of literature on smart products, smart services, and smart service systems, a consensus about what characteristics constitute the smartness of service systems is lacking. To conceptualize smartness (by identifying the characteristics that describe how smart a service system is), we engaged in a systematic literature review with an inductive analysis of definitions and/or descriptions of smart products, smart services, and smart systems in 57 papers in the marketing,

management, and computer literature. Across all definitions and descriptions, we identified four smartness characteristics: awareness, connectivity, actuation, and dynamism (see Table 1 for descriptions and key quotes derived from our inductive analysis). As shown in the last column of Table 1, each of these characteristics is essential and thus needs to be present for service systems to be smart. The next paragraphs detail each of these characteristics.

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Insert Table 1 about here

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A first characteristic of smartness is *awareness*, which refers to the ability to sense information related to the smart service system and/or its surroundings (Hsu & Lin, 2016; Töytäri et al., 2018; Wunderlich et al., 2015). This information is captured through sensors embedded in the smart service system (Mani & Chouk, 2016; Rijdsdijk & Hultink, 2009). Volvo’s smart car service, for instance, can sense data about itself (e.g., parts that need maintenance, its location) and its surroundings (e.g., bumps in the road, weather conditions).

A second characteristic of smartness is *connectivity*, which encompasses the ability to connect – through the Internet of Things (IoT) – different actors in the smart service system, namely customers, smart products, and service providers (Atzori, Iera, & Morabito, 2010; Fischer et al., 2020; Kannan & Li, 2017; Ng & Wakenshaw, 2017; Verhoef et al., 2017). For example, a smart digital assistant such as Echo is able to link with numerous smart products (e.g., smart thermostat, smart watch) and service providers (e.g., grocery stores, retailers).

A third characteristic of smartness is *actuation*, which is the ability to decide and act independently based on computational processes (Hoffman & Novak, 2018; Verhoef et al., 2017). Computation refers to the analysis and processing of the data collected through the smart service system’s sensors. These computational processes enable smart service systems to make decisions and act without customer intervention (Lim & Maglio, 2018; Novak & Hoffman,

2018). Based upon these processes, a smart service like Gardena's Smart Water Control Set is able to decide when plants need water and to water plants without customer intervention.

Finally, smartness is characterized by *dynamism*, which refers to the ability to learn and adapt based upon the relational and cyclical nature of smart service systems (Beverungen et al., 2019; Dreyer, Olovotti, Lebek, & Breitner, 2019; Hoffman & Novak, 2018; Kabadayi et al., 2019). This nature is reflected by ongoing interactions among actors in the smart service system, thereby enabling smart products and service providers to learn customer preferences and to adapt their smart services over time (Mani & Chouk, 2018; Novak & Hoffman, 2018). For example, smart thermostats (e.g., Ecobee4) learn customers' preferred room temperature based upon multiple interactions, thereby enabling the adaptation of the temperature depending on the customer(s) present in the room.

Based upon these four characteristics of smart service systems that are inherently linked to one another (see Table 1), different levels of smartness emerge. In fact, the smartness of service systems can vary from low (low levels of awareness, connectivity, actuation, and dynamism) to high (high levels of awareness, connectivity, actuation, and dynamism). As many product and service providers are increasing the smartness of their offerings (Beverungen et al., 2019; Chouk & Mani, 2019; Langley et al., 2020), we examine smartness as a key differentiator in the smart service market with implications for customer well-being through customer engagement.

2.2 Smartness as an Enabler of Customer Engagement

This section develops hypotheses about the relationship between smartness and customer engagement with the smart product and the service provider in the smart service system. To examine the smartness–engagement relationship, we propose two important underlying mechanisms: personalization mechanisms and intrusiveness mechanisms. These mechanisms reflect complex interactions between customer perceptions (perceived personalization and

perceived intrusiveness) and their corresponding importance (respectively, customers' need for personalization and intrusiveness sensitivity) (see Figure 1). Below, we first describe customer engagement in the context of smart service systems. Next, we explain the smartness–engagement relationship and its underlying mechanisms. Subsequently, we elaborate on customer well-being in smart service system contexts and substantiate the relationship between customer engagement and customer well-being. Figure 1 visually depicts these relationships.

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2.2.1 Customer engagement and its manifestations in the context of smart service systems

Customer engagement has been conceptualized by some authors as a psychological or motivational state, which reflects the customer's cognitive and emotional processing based on interactive experiences with a brand or firm (Bowden, 2009; Brodie, Hollebeek, Juric, & Ilić, 2011). Other researchers centered on the behavioral manifestations of customer engagement, which relate to more observable actions such as word-of-mouth and helping other customers or employees (Roy, Shekhar, Lassar, & Chen, 2018a; Rutz, Aravindakshan, & Rubel, 2019; van Doorn et al., 2010; Verleye, Gemmel, & Rangarajan, 2014). Synthesizing these two perspectives, an increasing number of researchers have adopted a transcending perspective (e.g., Brodie, Ilic, Juric, & Hollebeek, 2013; Pansari & Kumar, 2017). Adopting this transcending perspective, we consider customer engagement as a psychological or motivational state with cognitive, affective, and behavioral manifestations. Hence, customer engagement is a multidimensional concept (Harrigan, Evers, Miles, & Daly, 2018; Hollebeek et al., 2014). Building upon this conceptualization, the cognitive dimension refers to a customer's mental processing related to interactions with a particular firm or brand. The affective dimension describes the degree of emotions a customer experiences towards the firm or brand. The

behavioral dimension is defined as the customer's amount of energy, time, and effort allocated to interactions with the firm or brand (Hollebeek et al., 2014).

It has been widely recognized that customer engagement can go beyond dyadic interactions with a brand or firm (Alexander et al., 2017). Indeed, customers often have multiple actors to whom their engagement can be directed (Brodie, et al., 2019; Jaakkola & Alexander, 2014; Roy et al., 2018a; Verleye et al., 2014). This multi-actor engagement situation is inherent to the context of smart service systems (Barile & Polese, 2010; Hoffman & Novak, 2018), by which smart service systems refer to the configuration of smart products and service providers that are responsible for delivering smart services (Beverungen et al., 2019). Indeed, smart products may act as engagement objects for customers, as they enable the delivery of smart services (Anke, 2019; Beverungen et al., 2019; Fischer et al., 2020; Porter & Heppelmann, 2014). Many consumers, for instance, cannot live without their smartphone, as these devices give immediate access to contacts while also facilitating daily activities like shopping (Horwood & Anglim, 2019; Nie, Wang, & Lei, 2020). As a result, customers build relationships with these smart products (Novak & Hoffman, 2018; Schweitzer et al., 2019). In a similar vein, customers can engage with service providers whose services are enabled by smart products (Allmendinger & Lombreglia, 2005; Wunderlich, Wangenheim, & Bitner, 2013; Wunderlich et al., 2015). Social media companies, for instance, can elicit engagement by allowing customers to connect with one another and the same is true for retailers offering checkout-free shopping and other services via an app (David et al., 2018; Fan, Ning, & Deng, 2020).

As illustrated by these examples, customers can engage with both smart products and service providers in the smart service system. The next paragraphs detail how personalization mechanisms and intrusiveness mechanisms explain the relationship between smartness and customer engagement with the smart product and the service provider.

2.2.2 Smartness–engagement relationship explained by personalization mechanisms

Drawing from social exchange theory (Blau, 2017), several researchers argue that customers show engagement when brands or firms demonstrate investments beyond their mere economic obligations (Cropanzano & Mitchell, 2005; Hollebeek, 2011; Marchand, Paul, Hennig-Thurau, & Puchner, 2017; Verleye et al., 2014). For instance, investments in online brand communities or social media platforms were found to strengthen customer–firm relationships if firms listen to their customers and allow for two-way communication (Roy et al., 2018a; Shao, Jones, & Grace, 2015). Recent work on customer engagement also supports the fundamentals of social exchange theory by showing that customers are more likely to engage with brands or firms if they receive valuable resources in return (Guo, Zhang, & Sun, 2016; Harrigan et al., 2018; Roy et al., 2018a). This research contends that customers receive more valuable resources if companies advance the smartness of their service system, in that higher levels of smartness increase the perceived personalization (Kabadayi et al., 2019; Porter & Heppelmann, 2014; Roy et al., 2017). Here, perceived personalization refers to the extent to which customers experience that smart offerings are tailored to their specific needs and preferences (Roy et al., 2017; Xu et al., 2011). Indeed, more personalized services are generated if smart service systems capture more private information about the customers (i.e., awareness), increasingly share this information with connected actors (i.e., connectivity), decide and act more independently (i.e., actuation), and better learn and improve the service over time (i.e., dynamism) (Beverungen et al., 2019; Dreyer et al., 2019). Hence, we predict that higher levels of smartness go along with higher levels of perceived personalization by customers, which in turn boost customer engagement with smart service system actors.

In smart service systems, smart products and service providers perform different roles (Beverungen et al., 2019). More specifically, the smart product plays a more central role because it is the channel through which service providers enter customers' lives. Following the

central role of the smart product in smart service systems along with its tangible nature (i.e., smart products as combination of physical and digital components - Anke, 2019; Beverungen et al., 2019; Porter & Heppelmann, 2014), customers are more likely to return their engagement in response to personalized services to the smart product rather than to the service provider in the smart service system. Prior research confirms that customers ascribe efforts – such as investments in higher levels of smartness to provide more personalized services – mainly to the most visible actor (Kranzbühler, Kleijnen, & Verlegh, 2019). As the smart product is the most visible actor in the smart service system, customers are more likely to engage with it than with other actors (here, service providers) in the smart service system when more personalized services are offered through higher levels of smartness. Therefore, we hypothesize the mediating role of perceived personalization as follows:

H1a: Increased levels of smartness lead to more customer engagement with the smart product and the service provider in the smart service system through perceived personalization.

H1b: The positive effect of smartness through perceived personalization on customer engagement is stronger for the smart product relative to the service provider in the smart service system.

Despite the positive impact of personalized services on customer engagement, not all customers may have the same needs in terms of personalization. In other words, receiving personalized services or products is not equally important for all customers (Herbas Torrico & Frank, 2019; Shen & Dwayne Ball, 2009). In fact, customer traits – such as the need for personalization – influence a wide variety of customer outcomes (Dabholkar & Bagozzi, 2002; Meuter, Bitner, Ostrom, & Brown, 2005), including customer engagement with brands or firms (Islam, Rahman, & Hollebeek, 2017; Shen & Dwayne Ball, 2009). Building upon this line of

thought, we contend that customer engagement with smart service system actors is shaped by a customer's need for personalization. We define the need for personalization as a customer's desire for products and services that resemble the customer's specific needs and preferences (Herbas Torrico & Frank, 2019; Xu et al., 2011). As customers with a high need for personalization are found to value investments of actors in personalized services more than those with a low need for personalization (Herbas Torrico & Frank, 2019), we expect – in line with social exchange theory – that the effect of personalization on customer engagement with different actors in the smart service system is stronger for customers with a high (versus a low) need for personalization. Therefore, we hypothesize the moderating role of the need for personalization as follows:

H2: The positive effect of perceived personalization on customer engagement with the smart product and the service provider in the smart service system is stronger for customers with a high versus a low need for personalization.

2.2.3 Smartness–engagement relationship explained by intrusiveness mechanisms

To achieve more personalized services through higher levels of smartness, companies need to gather more personal information (i.e., awareness), increasingly share this information with other actors (i.e., connectivity), more extensively employ this information to execute tasks more independently (i.e., actuation), and increasingly exploit this information to better learn and adapt the smart offering (i.e., dynamism) (Mani & Chouk, 2016; Dreyer et al., 2019). Although the usage of personal information may increase perceived personalization and hence lead to more engagement with smart service systems, extant research in the context of personalized advertising suggests that these practices may also induce feelings of intrusiveness (Edwards, Li, & Lee, 2002; Gutierrez, O'Leary, Rana, Dwivedi, & Calle, 2019; van Doorn &

Hoekstra, 2013). Perceived intrusiveness refers to customers' experience that smart products or services are interfering with their life (Edwards et al., 2002; Mani & Chouk, 2016). Past literature demonstrates that these interferences increase when customers notice that their personal information is being used by companies (Edwards et al., 2002; Mani & Chouk, 2016; Papa, Mital, Pisano, & Del Giudice, 2020; Wottrich, van Reijmersdal, & Smit, 2018). As increases in the level of smartness of service systems imply more and more gathering, sharing, employing, and exploiting of personal data, we predict that higher levels of smartness generate increased perceptions of intrusiveness among customers. In turn, this provoked perceived intrusiveness can decrease customer engagement with smart service systems. Indeed, social exchange theory suggests that customer engagement is threatened when customers do not feel cared for or supported by service system actors (Cropanzano & Mitchell, 2005; Verleye et al., 2014). This situation is more likely to emerge when service systems with higher levels of smartness increasingly intrude into customers' lives by gathering, sharing, employing, and exploiting more and more personal information.

As mentioned before, smart service systems consist inherently of different types of actors – that is, smart products and service providers – which perform different roles (Beverungen et al., 2019). While the more central role of smart products along with their tangible nature positions them as the main responsible actor for perceived personalization, they may also be perceived as the main culprit for heightened levels of perceived intrusiveness among customers (Kranzbühler et al., 2019). Hence, customers are expected to blame the smart product more than the service provider for perceived intrusions, resulting in more customer engagement towards the smart product than towards the service provider. Hence, we hypothesize the mediating role of perceived intrusiveness as follows:

H3a: Increased levels of smartness lead to less customer engagement with the smart product and the service provider in the smart service system through perceived intrusiveness.

H3b: The negative effect of smartness through perceived intrusiveness on customer engagement is stronger for the smart product relative to the service provider in the smart service system.

Meanwhile, prior research suggests that not all customers are equally sensitive to the use of personal information and hence intrusions into their lives (van Doorn & Hoekstra, 2013). Therefore, we propose intrusiveness sensitivity – that is, the extent to which customers are receptive for intrusions into their lives (Gutierrez et al., 2019; Luna Cortés & Royo Vela, 2013) – as an important customer trait in the context of smart services. As mentioned before, customer traits like intrusiveness sensitivity have been demonstrated to affect numerous customer outcomes including customer engagement (Dabholkar & Bagozzi, 2002; Meuter et al., 2005; Shen & Dwayne Ball, 2009; Islam et al., 2017). More specifically, we expect that the impact of the level of smartness on the perceived intrusiveness is stronger for customers who are more sensitive to intrusions into their lives. Therefore, we hypothesize the moderating role of intrusiveness sensitivity as follows:

H4: The positive effect of smartness on perceived intrusiveness is stronger for customers with a high versus a low level of intrusiveness sensitivity.

2.3 Customer Well-Being Implications of Engaging with Smart Service Systems

2.3.1 Customer well-being and its manifestation in the context of smart service systems

Customer well-being refers to the customer's optimal psychological condition (Ryan & Deci, 2001). Detractions from this optimal psychological condition are labeled as customer ill-being, which turns customer ill-being into the counterpart of customer well-being (Deci & Ryan,

2000). As widely acknowledged in the well-being literature, customer well-being incorporates both eudaimonic facets (i.e., extent of self-realization) and hedonic facets (i.e., extent of happiness and pleasure) (Anderson et al., 2013; Ryan & Deci, 2001). According to Ryan and Deci (2001), eudaimonic and hedonic facets are complementary facets of well-being that together provide an extensive picture of a person's psychological condition.

In the context of smart service systems, it has been illustrated that both facets are relevant (e.g., Horwood & Anglim, 2019; Howells, Ivtzan, & Eiroa-Orosa, 2016). With regard to the eudaimonic facet, extant research suggests – in line with self-determination theory – that customers need to believe that they have the competencies necessary to use smart service systems and hence have the abilities to use smart service systems, which is also labeled as self-efficacy (Bandura, 1977; Schweitzer & Van den Hende, 2016). As such, self-efficacy reflects customer well-being (La Guardia, Ryan, Couchman, & Deci, 2000; Ryan & Deci, 2001). Regarding the hedonic facet, a number of studies point out that anxiety to use new technologies (hereafter, technology anxiety) may mitigate the potential pleasure of using smart service systems (Mani & Chouk, 2018; Touzani, Charfi, Boistel, & Niort, 2018; Yang & Forney, 2013). Technology anxiety refers thus to feeling apprehensive when being faced with the possibility to use new technology-based, which makes customers avoidant towards technology-enabled services in general (Jokisch, Schmidt, Doh, Marquard, & Wahl, 2020). These higher avoidance motivations reduce customers' competence (Eliot & Sheldon, 1997), which resonates – in accordance with self-determination theory – with reduced customer well-being (La Guardia et al., 2000; Ryan & Deci, 2001; Touzani et al., 2018). Drawing on this reasoning, technological anxiety is an important inhibitor of customer well-being – and thus a provoker of customer ill-being – in a smart service system context (Gelbrich & Sattler, 2014; Ryan & Deci, 2000; Touzani et al., 2018). Building upon the aforementioned evidence, self-efficacy

and technology anxiety are important facets of customer well-being in the context of smart service systems.

2.3.2 Customer engagement–well-being relationship in the context of smart service systems

While customer well-being is considered as relatively stable, Diener, Lucas, and Scollon (2006) argue that some events or experiences can alter customers' well-being. In this regard, recent research suggests that customer well-being can be influenced by customers engagement with smart service systems actors (Lee et al., 2017; Nie et al., 2020; Rotondi, Stanca, & Tomasuolo, 2017). Indeed, customer engagement provides a platform through which well-being can be affected (e.g., David et al., 2018; Horwood & Anglim, 2019; Mende & van Doorn, 2015; Roy et al., 2017).

Building upon this line of thought, we contend that engaged customers think about, feel about, and use smart service systems in a more intense way (Bowden, Conduit, Hollebeek, Luoma-aho, & Solem, 2017; Hollebeek et al., 2014). As such, increased customer engagement with smart service system actors (here, smart product and service provider) can enable customers to improve their mastery of skills to use smart service systems. Drawing from the self-efficacy paradigm of Bandura (1977), the mastery of these smart service system skills enhances customers' self-efficacy, which resonates – in accordance with self-determination theory – with customer well-being (La Guardia et al., 2000; Ryan & Deci, 2001). As higher levels of self-efficacy are expected to follow from increased customer engagement with smart service system actors, we hypothesize:

H5: Increased levels of customer engagement with the smart product and the service provider in the smart service system lead to higher levels of self-efficacy among customers.

Meanwhile, technology anxiety – which is another important facet of customer well-being in smart service systems (here, smart product and service provider) – might also be influenced when customers engage with smart service system actors. More particularly, the more customers engage with ever smarter service systems, the more experience with a specific technology-enabled service is established. This experience with a specific technology-based service (here, smart service systems) may – as outlined in technology anxiety research – make customers less apprehensive to use new technology-based services in general. These lower levels of avoidance towards technology in general reflect diminished levels of technology anxiety (Chua et al., 1999; Niemelä-Nyrhinen, 2007). Therefore, we contend that increased customer engagement with smart service system actors can result in lower levels of technology anxiety (Jokisch et al., 2020), which resonates – in accordance with self-determination theory – with reduced customer ill-being and thus enhanced customer well-being (Deci & Ryan, 2000; La Guardia et al., 2000). Building upon this aforementioned reasoning, we hypothesize:

H6: Increased levels of customer engagement with the smart product and the service provider in the smart service system lead to lower levels of technology anxiety among customers.

3. Empirical Studies

The main empirical study tests our hypotheses regarding the effect of smartness on customer well-being through customer engagement with the smart product and the service provider in the smart service system, while taking personalization mechanisms and intrusiveness mechanisms into consideration. As background to this scenario-based study, an exploratory study develops and evaluates (i.e., manipulation and realism) scenarios that manipulate the distinct level of smartness of the smart service system.

3.1 Exploratory Study: Scenario Development

3.1.1 Research context and design

To develop the manipulations of smartness, this exploratory study builds on the insights from our systematic literature review. Based upon this review, we identified awareness, connectivity, actuation, and dynamism as the four inherently linked characteristics of smartness of service systems (see Table 1). Hence, we created scenarios with low versus high levels of awareness, connectivity, actuation, and dynamism to manipulate the level of smartness. To investigate scenario manipulation and realism, we conduct a scenario-based, between-subject experiment.

In all scenarios, participants read that they had bought a smart fridge that offers smart services. This smart fridge setting was deliberately chosen as the household penetration of smart home appliances is very high and predicted to keep growing exponentially over the upcoming years (Statista, 2020). Specifically, the participants read that the smart fridge is able to compose a grocery list and to order these groceries at the customer's preferred grocery store. In this context, a smart product (here, smart fridge) and a service provider (here, grocery store) constitute the smart service system. The low smartness scenario represents a smart service system characterized by low awareness, connectivity, actuation, and dynamism, while high levels of these smartness characteristics are present in the high smartness scenario (see Table 2 for detailed scenario descriptions). To verify whether the low smartness scenario still meets the criteria of smart service systems (i.e., four smartness characteristics), we also developed a "no smartness" scenario describing a smart fridge without smartness characteristics.

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After reading the scenario, the respondents received a questionnaire in which they were asked to evaluate the realism of the scenarios on a 7-point Likert scale by means of three items adopted from the literature (Dabholkar & Bagozzi, 2002; Van Vaerenbergh, Vermeir, & Larivière, 2013): "What is described in this scenario could also happen in real life", "The

scenario seems realistic”, and “I had no difficulty imagining myself in the situation” ($\alpha = 0.834$). Next, the respondents also evaluated the smartness manipulation with an overall smartness item (“According to you, how smart is this fridge?”, ranging from zero to hundred). Additionally, we measured the four smartness characteristics (see Appendix) using scales proposed in Rijdsdijk, Hultink, and Diamantopoulos (2007) and Rijdsdijk and Hultink (2009).

3.1.2 Data collection and sample statistics

Data was collected by means of Mechanical Turk (MTurk). Via this platform, the questionnaire was presented to U.S. citizens, as the penetration of smart home services in the U.S. is the highest worldwide and continuously keeps increasing (Statista, 2020). Specifically, 150 participants were randomly assigned to one of three experimental conditions (no smartness, low smartness, high smartness). In line with the recommendation for using MTurk as a sampling method (Crump, McDonnell, & Gureckis, 2013; Goodman & Paolacci, 2017), we performed the following actions: (1) paying an appropriate remuneration to encourage the respondents to fill out the questionnaire accurately (i.e., \$2), (2) paying every respondent even if the results could not be used, (3) pilot-testing the questionnaire ($n = 8$) to avoid misinterpretation and improve clarity, (4) asking respondents with an approval rate on MTurk of 95% or higher, and (5) monitoring MTurk forums to screen for information being shared regarding the survey (Goodman & Paolacci, 2017; Paolacci, Chandler, & Ipeirotis, 2010). After excluding three respondents who incorrectly filled in the control question, the final sample included 147 viable responses ($M_{age} = 36.89$; 62.50% male) with 49 respondents in the no smartness condition, 50 in the low smartness condition, and 48 in the high smartness condition.

3.1.3 Results

The results indicate that the realism of the three scenarios – no smartness ($M = 4.46$; $SD = 1.70$), low smartness ($M = 5.60$; $SD = 1.13$), and high smartness ($M = 5.59$; $SD = 1.32$) – is

above the midpoint ($p = 0.000$). In addition, the realism of the low and high smartness is significantly higher than 5 ($p = 0.000$), resulting in very realistic and easy to imagine scenarios (Dabholkar, 1996; Giebelhausen, Robinson, Sirianni, & Brady, 2014). With regard to the smartness manipulation, the analysis of variance revealed that the high smartness scenario is significantly different from the low smartness scenario ($M_{overall} = 87.94$ versus 63.86; $M_{awareness} = 5.92$ versus 4.40; $M_{connectivity} = 5.99$ versus 3.53; $M_{actuation} = 5.31$ versus 3.38; $M_{dynamism} = 5.86$ versus 3.58). The low smartness scenario is, in turn, statistically different from the no smartness scenario ($M_{overall} = 19.47$; $M_{awareness} = 2.14$; $M_{connectivity} = 1.98$; $M_{actuation} = 2.21$; $M_{dynamism} = 2.17$).

3.1.4 Discussion

The results of our exploratory study demonstrate that the low and high smartness scenarios differ in terms of smartness. In addition, these scenarios were perceived as realistic and easy to imagine. Moreover, the low smartness scenario differs from the no smartness scenario, thereby demonstrating that the low smartness scenario still meets the criteria of a smart service system (i.e., the four smartness characteristics). As this research aims to provide insight into smartness as an enabler of customer well-being through customer engagement and its underlying mechanisms, we will compare the low and high smartness scenario in the main study.

3.2 Main Study

3.2.1 Research design and sample

To test the hypotheses depicted in the conceptual model (see Figure 1), we conducted a scenario-based, between-subjects experiment. In this experiment, respondents were randomly assigned to the low or the high smartness conditions developed in the exploratory study. Afterwards, the respondents filled out a questionnaire about their well-being (here, self-efficacy and technology anxiety), their engagement with the smart product and the service provider, and their perceptions (here, perceived personalization and perceived intrusiveness)

along with their corresponding importance (here, need for personalization and intrusiveness sensitivity), thereby using validated scales from the literature (see Appendix). For self-efficacy and customer engagement, a selection of the original items was used – in line with previous smart service system and engagement literature in smart service contexts (e.g., Fan et al., 2020; Islam et al., 2017; Mani & Chouk, 2016, 2018) – to ensure the fit with our smart fridge context and our scenario-based design. In addition, the questionnaire also included age, gender, and education level, as these control variables were found to influence customer engagement and customer well-being in previous research (Horwood & Anglim, 2019; Islam, Hollebeek, Rahman, Khan, & Rasool, 2019). All items were measured on 7-point Likert scales. After excluding the respondents that answered the control questions incorrectly, the final sample included 730 respondents ($M_{age} = 35.88$; 56.6% male) with 362 respondents in the low smartness condition and 368 respondents in the high smartness condition.

3.2.2 Methodology

To assess the impact of a low versus a high level of smartness on customer well-being through (1) customer perceptions and their associated importance and (2) customer engagement with the smart product and the service provider in the smart service system, we used a mediation approach (Zhao, Lynch Jr, & Chen, 2010) with Bayesian estimation (Yuan & MacKinnon, 2009) in Mplus. In line with Gelman and Rubin (1992), we ran three independent Markov Chain Monte Carlo (MCMC) chains with different starting points and 100,000 iterations each, by which the first half is considered as the “burn-in” phase and the remaining half is used to estimate the posterior distribution for the parameters. To assess the convergence of the MCMC algorithm, we inspected the Gelman-Rubin convergence statistic R , autocorrelation plots, and trace plots of the residual variance for the parameter estimates. Specifically, given the last 50,000 iterations (used to estimate the parameters), the largest value of the Gelman-Rubin convergence statistic R ranged between 1.002 and 1.009 (note that Yuan and MacKinnon

(2009) have suggested that a value of R close to 1 [the highest cut-off being 1.2] is an indication of reasonable convergence). Hence, this investigation provided evidence of the MCMC algorithm's convergence.

As suggested by Iacobucci (2008) and Yuan and MacKinnon (2009), the following equations were jointly estimated using structural equation modeling (SEM) in order to test our proposed conceptual model:

$$CWB_{iw} = \beta_{0w} + \beta_{1w \rightarrow 3w} CV_i + \beta_{4wd} CE_{id} + \varepsilon_{iw} \quad (1)$$

$$CE_{id} = \beta_{5d} + \beta_{6d} SMART_i + \beta_{7d} PP_i + \beta_{8d} PI_i + \beta_{9d} NP_i + \beta_{10d} PP_i \times NP_i + \xi_{id} \quad (2)$$

$$PP_i = \beta_{11} + \beta_{12} SMART_i + \epsilon_i \quad (3)$$

$$PI_i = \beta_{13} + \beta_{14} SMART_i + \beta_{15} IS_i + \beta_{16} SMART_i \times IS_i + e_i \quad (4)$$

in which CWB_{iw} denotes the customer well-being of individual i ($i = 1$ to 730) for well-being dimension w , in which two dimensions ($w = 1$ to 2) are jointly modeled: self-efficacy (SE) and technology anxiety (TA) respectively. CE_{id} denotes the customer engagement of individual i for engagement dimension d , in which six dimensions are discerned ($d = 1$ to 6): cognitive, affective, and behavioral engagement with the smart product, and cognitive, affective, and behavioral engagement with the service provider respectively. ε_{iw} , ξ_{id} , ϵ_i and e_i are the error terms with intercorrelation ρ and CV_i is a vector of the control variables (age, gender, and education level).

To test H1a and H1b, we used – in line with prior research (e.g., Larivière et al., 2016) – the widely adopted procedure of Zhao et al. (2010). In accordance with Zhao et al.'s (2010) procedure, an additional parameter estimate for the mediating influence of perceived personalization is calculated. Specifically, the impact of smartness on customer engagement via the mediation of perceived personalization is defined as a new parameter (by means of the “model constraint” function in Mplus; see Muthén, 2010, p. 7) by multiplying the obtained estimate of the direct effect of smartness ($SMART_i$) on perceived personalization (PP_i) (i.e.,

β_{12}) with the obtained direct effect of perceived personalization on customer engagement (CE_{id}) (i.e., β_{7d}) (Zhao et al., 2010). Meanwhile, β_{10d} represent the parameter estimates of the moderating influence that need for personalization (NP_i) has on the relationship between perceived personalization (PP_i) and customer engagement with the smart product and the service provider (CE_{id}), to test H2. In a similar vein as H1a and H1b, we test H3a and H3b according to the procedure of Zhao et al. (2010) by multiplying the obtained estimate of the direct effect of smartness ($SMART_i$) on perceived intrusiveness (PI_i) (i.e., β_{14}) with the obtained direct effect of perceived intrusiveness (PI_i) on customer engagement (CE_{id}) (i.e., β_{8d}). To assess H4, β_{16} represents the moderating influence of intrusiveness sensitivity (IS_i) on the relationship between the level of smartness ($SMART_i$) and perceived intrusiveness (PI_i). Finally, parameters β_{4wd} represent the direct influence of the six customer engagement dimensions (CE_{id}) on the two customer well-being dimensions – here, self-efficacy (CWB_{iw1}) and technology anxiety (CWB_{iw2}) – to test H5 and H6.

The paths as specified in equations 1 to 4 are modelled in combination with the measurement model. Hence, latent variables are used for the key constructs under investigation (i.e., CWB_{iw} , CE_{id} , PP_i , PI_i , NP_i , and IS_i) and measurement errors are accounted for in the modeling. Multicollinearity was assessed by means of variance inflation factors (VIF) and variable selection technique (VST). First, we ran ordinary least square (OLS) regressions to generate VIF values. All the VIF values of every variable in all equations were below the suggested cut-off value of 5 (i.e., highest VIF was 4.724 for equation 1, 1.566 for equation 2, and 2.000 for equation 4; see Hair, Black, Babin, & Anderson, 2010, p 204). Next, we ran a forward VST to further assure the absence of multicollinearity as this test assesses multicollinearity's degree and impact on our analysis (Chatterjee, Hadi, & Price, 2000). The results show that the VST model's parameter significance, sign, and magnitude correspond to

the full model results. On the basis of the VIF values and VST analyses, we conclude that multicollinearity is not a problem in our dataset (Chatterjee et al., 2000; Hair et al., 2010).

Common method bias (CMB) was assessed by means of the Harman's single-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) and the marker variable technique (Lindell & Whitney, 2001). The Harman's single-factor test makes use of exploratory factor analysis to check whether a single factor emerges or one general factor accounts for the majority of the covariance among the measures. The results showed ten factors, by which the first factor accounted for 28.11% of the variance and all factors together explained 78.38% of the variance. Hence, none of these factors accounted for the majority of the covariance among the items, providing us a first indication that CMB was not a serious threat to our analyses (Podsakoff et al., 2003). Second, we employed the marker variable technique (Lindell & Whitney, 2001) and used the marker variable (i.e., "satisfaction with living environment") as proposed by Yee, Yeung, and Cheng (2008). Since this marker variable is theoretically unrelated to the variables under investigation, CMB can be assessed based on the correlation between the marker variable and the research variables. The average size of the correlation (r_M) between the marker variable and key constructs was found to be 0.148, which is below the cut-off of 0.260 that is suggested and based on Malhotra, Kim, and Patil's (2006, p. 1873) sensitivity analysis. Additionally, as outlined by Ye, Marinova, and Singh (2007), we ran an alternative model in which we partialled out potential CMB problems by controlling for the marker variable in all equations. Our results indicated that none of the variables (both significance level and parameter magnitude) were affected by the inclusion of the marker variable. Based on the results from the Harman's single-factor test and the marker variable technique, we conclude that CMB is not a significant concern in our dataset (Lindell & Whitney, 2001; Podsakoff et al., 2003). Table 3 shows the results of the marker variable test and the descriptive statistics.

In addition, we conducted a confirmatory factor analysis (CFA; R Studio) to evaluate construct validity. The measurement model for the sample performed well. Indeed, the comparative fit index (CFI), 0.960, and Tucker-Lewis index (TLI), 0.955, were both above common benchmarks of 0.900. Furthermore, the root mean square error of approximation (RMSEA) was 0.038, which is below the advised level of 0.050, thereby reflecting a good fit (Hu & Bentler, 1999; Netemeyer, Bearden, & Sharma, 2003). The individual items and item loadings are presented in the Appendix. The sample showed convergent validity, since all construct reliabilities (CR) were above 0.60, which is considered to be a desirable construct reliability (Bagozzi & Yi, 1988) and all average variances extracted (AVE) exceeded 0.50 (see Appendix). Additionally, there is evidence for discriminant validity when comparing the square root of the AVE with the factor correlations (see Table 3) (Fornell & Larcker, 1981).

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Insert Table 3 about here

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3.2.3 Findings – Hypotheses testing

The extent to which the empirical results support the hypotheses is summarized in Table 4. The remainder of this section elaborates in detail upon the results related to each hypothesis.

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Insert Table 4 about here

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Table 5 presents the model estimates, which show that smartness has a positive significant effect on perceived personalization ($\beta_{12} = 0.530$). Moreover, our findings provide strong support for the positive impact of smartness on all customer engagement dependents through the mediation of perceived personalization (multiplying β_{12} and β_{7d} resulting in 0.285, 0.219, 0.241, 0.128, 0.139, 0.148 for respectively CE_{d1}, CE_{d2}, CE_{d3}, CE_{d4}, CE_{d5}, and CE_{d6}), thereby supporting H1a. The standardized parameter estimates of the indirect effect reveal that

these mediation mechanisms are much stronger for customer engagement dimensions with the smart product ($\beta_{12} \times \beta_{7d}$ is 0.285 for cognitive, 0.219 for affective, and 0.241 for behavioral engagement towards the smart product; i.e., respectively CE_{d1} , CE_{d2} , and CE_{d3}) compared to the respective customer engagement dimensions with the service provider ($\beta_{12} \times \beta_{7d}$ is 0.128, 0.139 and 0.148 for respectively cognitive, affective and behavioral engagement towards the service provider; i.e., respectively CE_{d4} , CE_{d5} , and CE_{d6}). Post-hoc significance tests (procedure outlined by Clogg, Petkova, & Haritou, 1995) further detail on the statistical differences with respect to the mediating impact of perceived personalization on customer engagement dimensions with the smart product versus customer engagement dimensions with the service provider. More precisely, these post-hoc tests reveal that the parameter estimates for this mediation mechanism ($\beta_{14} \times \beta_{8d}$) (i) for cognitive engagement with the smart product is significantly higher than cognitive engagement with the service provider (i.e., p -value is 0.000), (ii) for affective engagement with the smart product is significantly higher than affective engagement with the service provider (i.e., p -value is 0.007), and (iii) for behavioral engagement with the smart product is significantly higher than behavioral engagement with the service provider (i.e., p -value is 0.004). As such, H1b is supported.

In addition, Table 5 reveals that the parameter estimates (β_{10d}) for the moderating impact of need for personalization on the relationship between perceived personalization and customer engagement with the smart service system actors (β_{10d} is 0.100, 0.195, 0.190, 0.096, 0.121, and 0.067 for respectively CE_{d1} , CE_{d2} , CE_{d3} , CE_{d4} , CE_{d5} , and CE_{d6}) are significantly positive. The positive impact of perceived personalization on the customer engagement dimensions is thus found to be more pronounced in case of a higher need for personalization. Hence, H2 is supported.

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Insert Table 5 about here

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Regarding intrusiveness mechanisms, we observe that higher levels of smartness are also associated with higher levels of perceived intrusiveness ($\beta_{14} = 0.300$). This is statistically different ($p\text{-value} < 0.001$; Clogg et al., 1995) and almost half of the magnitude of the effect size that we observed for the impact of smartness on perceived personalization ($\beta_{12} = 0.530$). Furthermore, the additional calculated parameter estimates in Table 5 show that smartness has a significant indirect impact on all customer engagement dependents through the mediation of perceived intrusiveness (multiplying β_{14} and β_{8d}). More particularly, the estimates reveal that this mediation is negative for affective and behavioral customer engagement with the smart product ($\beta_{14} \times \beta_{8d}$ is -0.031 and -0.062 for respectively CE_{d2} and CE_{d3}) in line with our hypotheses. Interestingly, a significant, but positive mediation effect of perceived intrusiveness is found for cognitive customer engagement with the smart product ($\beta_{14} \times \beta_{8d}$ is 0.017 for CE_{d1}), as well as for cognitive, affective and behavioral customer engagement with the service provider ($\beta_{14} \times \beta_{8d}$ is 0.056 , 0.035 and 0.026 for respectively CE_{d4} , CE_{d5} and CE_{d6}). Therefore, H3a is only partly supported (i.e., only supported for CE_{d2} and CE_{d3}). Post-hoc tests (procedure outlined by Clogg et al., 1995) further reveal that the negative parameter estimates for this mediation mechanism ($\beta_{14} \times \beta_{8d}$) is significantly lower (i) for affective engagement with the smart product than affective engagement with the service provider (i.e., $p\text{-value}$ is 0.000), and (ii) for behavioral engagement with the smart product than behavioral engagement with the service provider (i.e., $p\text{-value}$ is 0.000). In contrast, for cognitive engagement with the smart product we observed a positive parameter estimate, whereas a negative parameter estimate was postulated. Therefore, H3a is only partly supported (i.e., only supported for CE_{d2} and CE_{d3}). In addition, we found strong evidence that the impact of smartness on perceived intrusiveness is moderated by customers' intrusiveness sensitivity, as hypothesized ($\beta_{16} = 0.158$). Therefore, H4 is supported.

Finally, the effect of customer engagement with smart product and the service provider in ever smarter service systems on customer well-being was assessed. Regarding self-efficacy, Table 5 shows that cognitive and behavioral customer engagement with the smart product have a positive effect on self-efficacy (β_{4w1d1} is 0.127 for cognitive CE_{d1} and β_{4w1d3} is 0.253 for behavioral CE_{d3}), while cognitive customer engagement with the service provider has a negative effect on self-efficacy (β_{4w1d4} is -0.099 for cognitive CE_{d4}). Meanwhile, the other customer engagement dimensions had insignificant effects on self-efficacy. Hence, H5 is partially supported. Concerning technology anxiety, the estimates reveal that behavioral customer engagement with the smart product has a negative effect on technology anxiety (β_{4w2d3} is -0.219 for behavioral CE_{d3}), while cognitive customer engagement with the service provider has a positive effect on technology anxiety (β_{4w2d4} is 0.159 for cognitive CE_{d4}). Meanwhile, the other customer engagement dimensions had insignificant effects on technology anxiety. These findings partially support H6.

3.2.4 Findings – Total effect of smartness on customer well-being via customer engagement

To evaluate the total effect of smartness on customer well-being¹, we performed three analyses (see respectively Panel A, B, and C in Table 6). First, we investigated the *total effect of smartness on customer engagement with smart products and service providers in smart service systems* by simultaneously considering the direct and indirect impact of smartness on the six customer engagement dependents. Panel A of Table 6 provides a summary of the total effect of smartness on customer engagement by cumulating the following three effects: (i) the direct effect of smartness on customer engagement (β_{6d}), (ii) the indirect effect of smartness on customer engagement through the mediation of perceived personalization ($\beta_{12} \times \beta_{7d}$), and (iii) the indirect effect of smartness on customer engagement through the mediation of perceived

¹ We thank the anonymous reviewer for drawing our attention to this point.

intrusiveness ($\beta_{14} \times \beta_{8d}$). Table 6 copies these three effects from Table 5, and further calculates the corresponding total effect of smartness on customer engagement with the smart service system actors (that is obtained by means of the “model constraint” function in Mplus; see Muthén, 2010, p. 7). The total effect estimates reveal that higher levels of smartness have a significant positive effect on customer engagement with the smart product (0.205 for cognitive, 0.058 for affective, and 0.071 for behavioral; i.e., CE_{d1} , CE_{d2} , and CE_{d3} ; all significant at p -value < 0.05). In contrast, the total effect of smartness on customer engagement with the service provider is found to be insignificantly different from zero (-0.041 for cognitive, 0.025 for affective, and -0.021 for behavioral; i.e., CE_{d4} , CE_{d5} , and CE_{d6} ; all p -values > 0.05).

Second, Panel B of Table 6 further details the *total effect of smartness on customer engagement while considering customers’ need for personalization and intrusiveness sensitivity*. Specifically, Panel B details this total effect in four situations in which customers’ need for personalization and intrusiveness sensitivity both vary between low and high. In case of high need for personalization – regardless of the level of intrusiveness sensitivity (i.e., situations 2 and 4) – we observe a stronger impact of the level of smartness on customer engagement with the smart product, as well as the emergence of a significant impact of smartness on affective engagement with the service provider compared to the population-averaged total effect reported in Panel A. In contrast, when need for personalization is low – regardless of the level of intrusiveness sensitivity (i.e., situations 1 and 3) – Panel B shows that smartness exhibits a weaker impact on customer engagement. Specifically, the impact of smartness on affective engagement with both the smart product and the service provider becomes insignificant and the impact of smartness on behavioral engagement with the smart product decreases in effect size, while the total effect of smartness on cognitive engagement with the smart product remains quite stable and still very high (i.e., comparing situations 1 and 3 with situations 2 and 4). Taken together, these insights of Panel B demonstrate that the total

effect of smartness on customer engagement not only depends on the mediating mechanisms, but also on the moderating influence of need for personalization. Note that beside these moderating influences, need for personalization and intrusiveness sensitivity also exert direct influences on customer engagement and perceived intrusiveness respectively (see respectively β_{9d} and β_{15} in Table 5).

Finally, we disentangle the *total effect of smartness on customer well-being* through the double mediation of customers' perceptions and engagement, thereby also accounting for customers' need for personalization and intrusiveness sensitivity. Panel C of Table 6 displays the total effect of smartness by multiplying (by means of the aforementioned "model constraint" function) the total effect of smartness on customer engagement (see Panel A and B for the estimates, respectively, with and without customers' need for personalization and intrusiveness sensitivity) with the effect of customer engagement on self-efficacy and technology anxiety (β_{4wd} from Table 5). First of all, Panel C (see first line) shows the total effect without accounting for customers' need for personalization and intrusiveness sensitivity. The results indicate that higher levels of smartness significantly enhance customer self-efficacy. Further, Panel C shows that a high need for personalization strengthens this positive relationship between the level of smartness and self-efficacy (see situations 2 and 4). Meanwhile, the total effect of the level of smartness on technology anxiety – when we do not account for customers' need for personalization and intrusiveness sensitivity – is negative, but not significant. Notably, this negative effect of the level smartness on technology-anxiety becomes marginally significant in case customers have a high personalization need and a low sensitivity to intrusions (see situation 2). In sum, these insights of Panel C reveal that (i) the total impact of the level of smartness on customer well-being primarily effectuates through self-efficacy in all situations, but is found to be more pronounced for customers with a high need for personalization, and (ii) the most optimal customer well-being implications (here, both

enhancing self-efficacy and lowering technology anxiety at the same time) of higher levels of smartness can be achieved when customers have a high need for personalization in tandem with a low intrusiveness sensitivity.

Insert Table 6 about here

3.3 Robustness Checks

We ran several robustness checks. First, we ran five models to show that we obtain similar findings for the focal effects (e.g., Van Heerde, Dinner, & Neslin, 2019), but only the last one (M5) is reported in this manuscript (see Table 5). Model 1 (M1) through model 4 (M4) – which are available upon request – are simpler models than model 5 (M5): M1 only included the control variables and the impact of customer engagement on customer well-being, M2 added the impact of smartness through the mediation of perceived personalization, M3 added the need for personalization, M4 added perceived intrusiveness, M5 added intrusiveness sensitivity. The results across all models with respect to the investigated parameter estimates remained very similar (in terms of signs, significance level, and effect sizes), thereby indicating the robustness of our parameter estimates.

Second, an additional model (M6) was assessed in which a marker variable was included to test for the potential influence of common method bias (Lindell & Whitney, 2001). Comparing M6 with M5 (our main model) provided evidence for stable parameter estimates.

Third, we compared the main model (M5) in which we used structural equation modeling (SEM) and Bayesian estimation with two more models: one model (M7) in which we employed frequentist analysis (i.e., maximum likelihood (ML) estimation in this case) instead of Bayesian statistics and another model (M8) in which we used path modeling (instead of SEM) with Bayesian estimation. The comparison of M7 and M5 discerned similar results in terms of signs, significance level, and effect sizes, thereby demonstrating evidence of stable

parameter estimates. This comparison revealed one small difference in p -values across the two models (M7 versus M5) with respect to the impact of perceived intrusiveness on cognitive customer engagement with the smart product (i.e., a p -value of 0.049 for M5, and a p -value of 0.075 for M7). Graphical inspection of the distribution of the posterior means for this parameter estimate (M5) revealed a distribution that approached a normal distribution, but not a perfect one. As Yuan and MacKinnon (2009) note, compared with conventional frequentist analysis (here, M7), the Bayesian approach (here, M5) does not impose restrictive normality assumptions on sampling distributions of estimates, making statistical inference straightforward and exact. As a result, we attribute this difference in p -values to this normality assumption and thus prefer M5 over M7.

In similar vein, the comparison of M8 and M5 discerned similar results in terms of signs, significance level, and effect sizes, thereby demonstrating evidence of stable parameter estimates. Additional post-hoc tests (Clogg et al., 1995) revealed that the observed differences between both models were not found to be statistically different from each other (lowest p -value is 0.480). While path analysis (here, M8) is a special case of SEM (here, M5), the main difference is that path analysis assumes that all variables are measured without error, whereas SEM uses latent variables to account for measurement error. Although SEM models requires more parameters to be estimated and thus may need more iterations to obtain model convergence, our main model (M5) converged satisfactorily. In addition, as the model findings did reveal evidence of significant measurement errors, M5 – the model that accounts for these measurement errors in the modeling – is preferred.

Finally, we estimated a last model (M9) without any endogeneity correction. Specifically, we restricted the correlation in the error terms of the customer well-being dependents to zero and excluded the control variables (e.g., Van Heerde et al., 2019). A

comparison with the main model (M5) revealed that the focal effects were replicated in terms of signs, significance, and effect sizes. As such, supporting the robustness of our model (M5).

4. General Discussion

4.1 Theoretical Implications

As companies are increasingly advancing the level of smartness of their service system (Langley et al., 2020), this research investigates the implications of higher levels of smartness for customer well-being through customer engagement and personalization and intrusiveness mechanisms. The findings contribute to smart service systems, customer well-being, and customer engagement literature in various ways.

4.1.1 Contributions to the smart service system literature

Based upon a systematic integration of a wide variety of smart product, smart service, and smart service system descriptions and definitions, this research identifies awareness, connectivity, actuation, and dynamism as key characteristics of smartness. By doing so, this research contributes to an important and ongoing debate in the smart service system literature about the definition of smartness (e.g., Langley et al., 2020; Lim & Maglio, 2018). Specifically, smartness is a multidimensional phenomenon, by which awareness, connectivity, actuation, and dynamism are inherently linked to one another. This multidimensional conceptualization of smartness allows researchers to better conceptualize and operationalize smartness in their work, as well as to reflect upon the level of smartness of their smart service systems.

By showing that the level of smartness influences customer well-being in smart service systems, this research also advances the smart service system literature where customer well-being only recently gained attention. Indeed, growing attention is devoted to customer well-being when using smartphones (e.g., David et al., 2018; Horwood & Anglim, 2019), smart wearables (e.g., Papa et al., 2020), and smart retail technology (e.g., Roy et al., 2017). While

these studies demonstrate that the usage of smart service systems can affect customer well-being, these studies have largely ignored the impact of smartness of these service systems on well-being. In other words, the level to which these service systems incorporate awareness, connectivity, actuation, and dynamism and its subsequent impact on customer well-being remained unclear. By addressing this theoretical gap, this research provides insight into the link between smartness and customer well-being (here, self-efficacy and technology anxiety).

4.1.2 Contributions to the Customer Well-Being Literature

To date, Hollebeek and Belk (2018) point out that scant knowledge exists on customer engagement with smart technology and its relationship with well-being. In response to this gap, the present research unravels the smartness–well-being relationship by investigating the mediating role of customer engagement. Specifically, this research shows that higher levels of smartness stimulate customer well-being through customer engagement with the smart product. Indeed, customer engagement with the smart product increases customers’ self-efficacy while decreasing their technology anxiety, thereby building on self-determination theory. Meanwhile, our empirical evidence suggests that customer engagement with service providers reduces customer well-being as it decreases customers’ self-efficacy and increases customers’ technology anxiety. By exposing how customer engagement influences customer well-being in terms of its eudaimonic facet (here, self-efficacy) as well as its hedonic facet (here, technology anxiety), this inquiry provides an extensive picture of the engagement–well-being relationship in the context of smart service systems.

As customer engagement with smart products has a different role with regard to the smartness–well-being relationship than customer engagement with service providers, this research also shows how the technological nature of smart service system actors may affect their impact on customer well-being. Specifically, smart products (e.g., smart fridge) are – in contrast with service providers such as a grocery store – technological in nature. By engaging

with technological actors like smart fridges, customers become – in line with the familiarity principle (Brown, Fuller, & Vician, 2004) – more acquainted with technology-based offerings, thereby stimulating their technology-related self-efficacy and even reducing their technology-related anxiety in general. In contrast, when customers are increasingly engaging with service providers like grocery stores, the technological aspects of the smart service system may become less salient and hence reduce customers' self-efficacy and increase their technology anxiety.

4.1.3 Contributions to the Customer Engagement Literature

By unraveling how customer perceptions along with their associated importance shape the smartness–engagement relationship in smart service systems, this research adds to the understanding of complex service systems as urged upon by engagement researchers (e.g., Alexander et al., 2017). Specifically, this study reveals that higher levels of smartness stimulate customer engagement with the smart product and even customer engagement with the service provider by offering personalization benefits (cf. mediating role of perceived personalization). As such, this study shows that personalization benefits are – in accordance with social exchange theory – an important driver of customer engagement with different actors in a service system (Roy et al. 2018a). Meanwhile, higher levels of smartness decrease – in line with social exchange theory – behavioral engagement with the smart product through intrusiveness perceptions (cf. mediating role of perceived intrusiveness). Although these intrusiveness perceptions increase cognitive engagement with the smart product, it is conceivable that customers think more about this actor as it is physically intruding into their lives. As customers may thus mainly perceive smart products – and not service providers – as central actors in smart service systems, service providers are not held responsible for intrusiveness perceptions. This is reflected by the absence of negative implications of intrusiveness perceptions for customer engagement with the service provider, which may thus stem from attribution

mechanisms. Indeed, Kranzbühler et al. (2019) suggest that both rewards and blames are primarily associated with the most visible actor (here, smart product).

Further inquiry unveils the necessity to not solely account for customer perceptions (here, perceived personalization and perceived intrusiveness), but also for the importance that customers attach to it (here, need for personalization and intrusiveness sensitivity) as the impact of these perceptions is found to be more pronounced when customers attach more importance to it (e.g., the influence of smartness on perceived intrusiveness is stronger for customers with higher intrusiveness sensitivity). As customer heterogeneity significantly influences the impact of smartness on customer well-being via customer engagement in smart service systems, it should be considered in future research on customer well-being and customer engagement.

4.2 Managerial Implications

This research helps managers to make more informed decisions about the level of smartness of their service systems in various ways. First, our conceptualization of smartness along its four inherently linked key characteristics (i.e., awareness, connectivity, actuation, and dynamism) provides managers involved in a smart service system with a framework to both design and evaluate the system's level of smartness. In addition, this study provides these managers with insights into the customer well-being implications of increasing the level of smartness. Specifically, they are advised to invest in higher levels of smartness, as these investments boost customer well-being. To further enhance customer well-being, these managers may also benefit from making customers' need for personalization more salient and their intrusiveness sensitivity less pronounced, for instance in advertisements about their smart service systems.

Second, this study aids managers to foster customer engagement with smart products, because higher levels of smartness stimulate cognitive, affective and behavioral engagement with smart products. Interestingly, the most optimal customer engagement returns are observed when customers report a high need for personalization, regardless of their intrusiveness

sensitivity. Hence, managers of smart products are advised to invest in all smartness characteristics (i.e., awareness, connectivity, actuation, dynamism) and clearly communicate about the personalization benefits of these smartness investments to their customers.

Third, this research also guides service providers about whether and how to be part of a smart service system. Overall, this research suggests that service providers benefit from forming service systems with higher levels of smartness, especially when their customers attach importance to personalized offerings. In those situations, customers may show more affective engagement towards the service provider. Hence, managers of service providers are also advised to communicate the personalization benefits when joining service systems with a high level of smartness or when investing in the smartness of service systems to which they belong.

4.3 Limitations and Future Research Directions

This study sheds light on the implications of higher levels of smartness for customer well-being through customer engagement and customer perceptions along with their associated importance. Some limitations, however, suggest directions for future research. First, the present research centered on smart service systems with low versus high smartness. Future research, however, could try to vary the level of smartness even more to detect curvilinear effects, similar to the uncanny valley effects related to the appearance of humanoid robots (Mori, 1970). Second, previous research also indicates that customer well-being can operate as a driver of customer engagement (e.g., Horwood & Anglim, 2019). Hence, it might be interesting for future research to investigate the reversed effect of well-being on customer engagement. Third, the present research focuses on smart service systems consisting of one smart product and one service provider. Future research can elaborate on customer engagement in the context of smart service systems in which more than two actors are involved. Here, researchers can explore how actors with different roles and positions in the smart service system can boost customer well-being in return for increasing the level of smartness. Fourth, a scenario-based experiment was

the most appropriate research design in this context, because service systems with high smartness are not commercialized yet. Nevertheless, a scenario-based experiment has its limitations in terms of gaining insight into the well-being implications (here, self-efficacy and technology anxiety) of increasing the level of smartness of service systems. Therefore, future research could use other research methods – such as field studies and field experiments – and take different well-being aspects – like belongingness or emotional health – into consideration. Finally, the empirical study examined one smart service system (here, smart fridge system) with respondents from one country (here, U.S.). As such, future research can explore the conditions under which customer engagement emerges in other settings and/or countries.

5. Concluding Thoughts – The Smarter, the Better?!

By empirically investigating the smartness–well-being relationship through customer engagement with different smart service system actors and the underlying mechanisms (here, customer perceptions and their corresponding importance), this research provides a detailed and nuanced reply to the compelling question “The smarter, the better?”. In sum, the overall answer is “The smarter, the better!” as higher levels of smartness (1) go along with personalization perceptions that exceed intrusiveness perceptions (2) through which especially cognitive, affective and behavioral customer engagement with the smart product is generated and to some extent even affective customer engagement with the service provider is generated, (3) which results in improved customer well-being (i.e., more self-efficacy and sometimes less technological anxiety) through the generated cognitive and behavioral customer engagement with the smart product, especially for customers with a high need for personalization.

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Tables and Figures

Table 1 – Smartness Characteristics and their Inherent Linkages

Smartness Characteristics	Description	Illustrative Evidence per Characteristic	Inherent Linkages between Four Smartness Characteristics
Awareness (AW)	The ability to sense information related to the smart service system and/or its surroundings.	“... must build intelligence-that is, awareness and connectivity-into the products themselves.” (Allmendinger & Lombreglia, 2005) “The key attributes of a smart technology are the ability to acquire information from the surrounding environment ...” (Marikyan, Papagiannidis, & Alamanos, 2019)	“A smart service system is a service system capable of learning, dynamic adaptation (D), and decision making (AC) [...] A smart service system is a service system that controls things for the users (AC) based on the technology resources for sensing (AW), connected network (C), context-aware computing (AC), and wireless communications (C).” (Lim & Maglio, 2018) “Smart services are enabled by smart products that are both connected (C) and intelligently aware (AW) to enable efficient operation, optimization, analysis, integration and other digitally-enabled business functions (AC; D)” (Klein, Biehl, & Friedli, 2018) “[...] “smart service” that is based on monitoring (AW), optimization (D), remote (C) control (AC), and autonomous (AC) adaptation of products (D)” (Beverungen et al., 2019) “These connected devices (C) can sense the surroundings (AW) and engage in real-time data collection (AW), communication (C), interaction (AC), and feedback (D)” (Roy, Balaji, Quazi, & Quaddus, 2018b)
Connectivity (C)	The ability to connect – through the Internet of Things (IoT) – different actors in the smart service system, namely customers, smart products, and service providers.	“... ability of smart objects to: (i) be identifiable (anything identifies itself), (ii) to communicate (anything communicates) and (iii) to interact (anything interacts) – either among themselves, building networks of interconnected objects, or with end-users or other entities in the network.” (Miorandi, Sicari, De Pellegrini, & Chlamtac, 2012) “Services provided based on the data from connected products are called “Smart Services” in this paper.” (Anke, Wellsandt, & Thoben, 2018)	
Actuation (AC)	The ability to decide and act independently based on computational processes.	“Smart services are IoT-based services that embody new capacities [...] autonomy (carrying out automatic actions without the user’s intervention)” (Mani & Chouk, 2018) “Smart products distinguish themselves from traditional products by their ability to process information” (Rijsdijk & Hultink, 2003)	
Dynamism (D)	The ability to learn and adapt based on the relational and cyclical nature of smart service systems.	“[...] smart services should be able to adapt based on changing customer and situational input.” (Kabadayi et al., 2019) “Smart services are individual, highly dynamic and quality-based service solutions...” (Dreyer et al., 2019)	

Table 2 – Smartness Scenarios

	Low Smartness Scenario	High Smartness Scenario
Intro	Imagine that you bought a SMART FRIDGE with the following service characteristics for ordering groceries AT YOUR PREFERRED GROCERY STORE:	
Connectivity	The smart fridge can connect with you via devices as smartphones and with another actor, namely your preferred grocery store. The smart fridge cannot connect with other actors, such as your garbage bin (that registers what you throw away including non-fridge food and beverages), your smart thermostat (that tracks weather and seasonal conditions), or social media (that gathers info about consumption trends).	The smart fridge can connect with you via devices as smartphones. The smart fridge can connect with other actors, such as your preferred grocery store, your smart garbage bin (that registers what you throw away including non-fridge food and beverages), your smart thermostat (that tracks weather and seasonal conditions), or social media (that gathers info about consumption trends).
Awareness	The smart fridge does use sensors to keep an eye on the products in the fridge (e.g., a box of eggs or a carton of milk). The smart fridge does not gather detailed information about the products (e.g., expiration dates) or text, audio and visual information communicated to the fridge by you or a household member, such as upcoming consumption needs, planned events or holidays.	The smart fridge does use sensors to keep an eye on the products in the fridge (e.g., a box of eggs or a carton of milk) or detailed information about the products (e.g., expiration dates). The smart fridge does gather text, audio and visual information communicated to the fridge by you or a household member, such as upcoming consumption needs, planned events or holidays.
Actuation	The smart fridge can propose a grocery list. You still have to add or remove items to the list. The smart fridge cannot send the grocery list to the grocery store. You still have to send the order to the grocery store.	The smart fridge can compose a grocery list. You have to do nothing. The smart fridge can send the grocery list to the grocery store. You have to do nothing.
Dynamism	The smart fridge does save one prior order. The smart fridge does not learn more about the household's habits, preferences and previous choices over time, such as consumption patterns, planned events or holidays, and seasonal trends.	The smart fridge does save all prior orders. The smart fridge does learn more about the household's habits, preferences and previous choices over time, such as consumption patterns, planned events or holidays, and seasonal trends.

Table 3 – Intercorrelations and Descriptive Statistics

Variables	Mean ¹	SD	CR	Cr. α	1	2	3	4	5	6	7	8	9	10	11	12
1. CE with Smart Product (cognitive) (CE _{d1})	5.05	1.29	0.88	0.88	<i>0.84</i>	0.64**	0.59**	0.46**	0.44**	0.40**	0.50**	0.37**	0.10**	-0.03	0.18**	0.01
2. CE with Smart Product (affective) (CE _{d2})	4.73	1.39	0.94	0.94	0.65**	<i>0.92</i>	0.86**	0.40**	0.55**	0.50**	0.39**	0.49**	-0.10**	-0.22**	0.19**	-0.05
3. CE with Smart Product (behavioral) (CE _{d3})	4.84	1.45	0.90	0.89	0.60**	0.86**	<i>0.90</i>	0.30**	0.49**	0.48**	0.40**	0.47**	-0.18**	-0.26**	0.22**	-0.08*
4. CE with Service Provider (cognitive) (CE _{d4})	4.35	1.41	0.87	0.86	0.48**	0.43**	0.32**	<i>0.77</i>	0.67**	0.56**	0.20**	0.23**	0.14**	-0.01	0.01	0.17**
5. CE with Service Provider (affective) (CE _{d5})	4.41	1.36	0.94	0.94	0.46**	0.56**	0.51**	0.68**	<i>0.91</i>	0.72**	0.26**	0.34**	0.08*	-0.04	0.07	0.10*
6. CE with Service Provider (behavioral) (CE _{d6})	4.59	1.34	0.81	0.81	0.41**	0.51**	0.50**	0.57**	0.73**	<i>0.82</i>	0.24**	0.33**	0.01	-0.04	0.07	0.09*
7. Perceived Personalization (PP)	5.13	1.42	0.92	0.92	0.51**	0.41**	0.42**	0.22**	0.28**	0.25**	<i>0.87</i>	0.32**	0.25**	-0.00	0.12**	0.02
8. Need for Personalization (NP)	5.12	1.28	0.94	0.94	0.40**	0.52**	0.50**	0.27**	0.37**	0.36**	0.34**	<i>0.89</i>	-0.13**	-0.28**	0.29**	-0.12**
9. Perceived Intrusiveness (PI)	3.12	1.67	0.96	0.96	0.10**	-0.10*	-0.17**	0.14**	0.08*	0.02	0.25**	-0.11**	<i>0.91</i>	0.53**	-0.20**	0.44**
10. Intrusiveness sensitivity (IS)	3.90	1.87	0.97	0.97	-0.04	-0.24**	-0.27**	-0.02	-0.05	-0.05	-0.02	-0.29**	0.52**	<i>0.93</i>	-0.13**	0.37**
11. Self-Efficacy (CWB _{w1})	5.87	0.99	0.85	0.85	0.19**	0.20**	0.23**	0.03	0.08*	0.09*	0.14**	0.30**	-0.19**	-0.14**	<i>0.86</i>	-0.51**
12. Technology Anxiety (CWB _{w2})	2.60	1.58	0.92	0.92	0.02	-0.03	-0.07	0.18**	0.11**	0.10**	0.03	-0.10**	0.44**	0.36**	-0.50**	<i>0.89</i>
13. Marker	5.31	1.44	n.a.	n.a.	0.17**	0.21**	0.18**	0.18**	0.19**	0.16**	0.15**	0.28**	0.03	-0.08*	0.09*	0.06

Note. CE = customer engagement; ¹ All variables are measured on a 7-point Likert scale; SD = standard deviation; CR = composite reliability; Cr. α = Cronbach's alpha; the diagonal (in italics) shows the square root of the AVE for each construct; the numbers below the diagonal represent the correlations among constructs; correlation after common method adjustment ($r_M = 0.148$) are reported above the diagonal.

* $p < 0.05$; ** $p < 0.01$ (two-tailed tests)

Table 4 – Overview of Hypotheses Testing Results

Hypotheses	Supported
H1a: Increased levels of smartness lead to more customer engagement with the smart product and the service provider in the smart service system through perceived personalization.	Supported Supported for cognitive, affective and behavioral engagement with the smart product and supported for cognitive, affective and behavioral engagement with the service provider.
H1b: The positive effect of smartness through perceived personalization on customer engagement is stronger for the smart product relative to the service provider in the smart service system.	Supported Supported for cognitive, affective and behavioral engagement with the smart product, and supported for cognitive, affective and behavioral engagement with the service provider.
H2: The positive effect of perceived personalization on customer engagement with the smart product and the service provider in the smart service system is stronger for customers with a high versus a low need for personalization.	Supported Supported for cognitive, affective and behavioral engagement with the smart product, and supported for cognitive, affective and behavioral engagement with the service provider.
H3a: Increased levels of smartness lead to less customer engagement with the smart product and the service provider in the smart service system through perceived intrusiveness.	Partially Supported - Supported for affective and behavioral engagement with the smart product; - Opposite effects are observed for cognitive engagement with the smart product, and for cognitive, affective, and behavioral engagement with the service provider.
H3b: The negative effect of smartness through perceived intrusiveness on customer engagement is stronger for the smart product relative to the service provider in the smart service system.	Partially supported - Supported for affective and behavioral engagement with the smart product; - Not supported for cognitive engagement with the smart product since a positive effect was observed in H3a.
H4: The positive effect of smartness on perceived intrusiveness is stronger for customers with a high versus a low level of intrusiveness sensitivity.	Supported
H5: Increased levels of customer engagement with the smart product and the service provider in the smart service system lead to higher levels of self-efficacy among customers.	Partially Supported - Supported for cognitive and behavioral engagement with the smart product; - An opposite effect is observed for cognitive engagement with the service provider; - No effects are observed for affective engagement with the smart product, and affective and behavioral engagement with the service provider.
H6: Increased levels of customer engagement with the smart product and the service provider in the smart service system lead to lower levels of technology anxiety among customers.	Partially Supported - Supported for behavioral engagement with the smart product; - An opposite effect is observed for cognitive engagement with the service provider; - No effects are observed for cognitive and affective engagement with the smart product, and affective and behavioral engagement with the service provider.

Table 5 – Bayesian Estimates for Smartness–Well-Being Relationship through Customer Engagement and Customer Perceptions

	Mechanisms		Customer Engagement (CE) with Smart Product			Customer Engagement (CE) with Service Provider			Customer Well-Being (CWB)	
	Perceived Personalization (PP)	Perceived Intrusiveness (PI)	Cognitive (CE _{d1})	Affective (CE _{d2})	Behavioral (CE _{d3})	Cognitive (CE _{d4})	Affective (CE _{d5})	Behavioral (CE _{d6})	Self- Efficacy (CWB _{w1})	Technology anxiety (CWB _{w2})
<u>Parameter Estimates</u>										
Intercept ($\beta_{11}, \beta_{13}, \beta_{5d}, \beta_{0w}$)	2.788*	1.517*	3.404*	3.170*	3.121*	2.777*	3.021*	3.171*	5.700*	1.098*
Drivers										
Smartness (SMART) ($\beta_{12}, \beta_{14}, \beta_{6d}$)	0.530*	0.300*	-0.097*	-0.131*	-0.108*	-0.225*	-0.148*	-0.195*		
Perceived personalization (PP) (β_{7d})			0.538*	0.414*	0.455*	0.242*	0.262*	0.280*		
Perceived intrusiveness (PI) (β_{8d})			0.057*	-0.102*	-0.207*	0.186*	0.115*	0.086*		
Need for personalization (NP) (β_{9d})			0.366*	0.535*	0.501*	0.324*	0.436*	0.427*		
Intrusiveness sensitivity (IS) (β_{15})		0.417*								
Cognitive – Smart product (CE _{d1}) (β_{4wd1})									0.127*	0.026
Affective – Smart product (CE _{d2}) (β_{4wd2})									-0.017	-0.014
Behavioral – Smart product (CE _{d3}) (β_{4wd3})									0.253*	-0.219*
Cognitive – Service provider (CE _{d4}) (β_{4wd4})									-0.099*	0.159*
Affective – Service provider (CE _{d5}) (β_{4wd5})									-0.028	0.042
Behavioral – Service provider (CE _{d6}) (β_{4wd6})									-0.005	0.098
Moderating effects										
Perceived personalization*Need for personalization (PPxNP) (β_{10d})			0.100*	0.195*	0.190*	0.096*	0.121*	0.067*		
Smartness*Intrusiveness sensitivity (SMARTxIS) (β_{16})		0.158*								
Control variables (CV)										
Age (β_{1w})									-0.085*	-0.015
Gender_Male (β_{2w})									0.059	-0.008
Education level (β_{3w})									-0.061*	0.166*
R²	0.281*	0.302*	0.397*	0.478*	0.511*	0.181*	0.260*	0.249*	0.129*	0.114*
<u>Additional Calculated Parameter Estimates</u>										
Mediating effects										
Smartness through mediation of perceived personalization (SMARTxPP) ($\beta_{12x}\beta_{7d}$)			0.285*	0.219*	0.241*	0.128*	0.139*	0.148*		
Smartness through mediation of perceived intrusiveness (SMARTxPI) ($\beta_{14x}\beta_{8d}$)			0.017*	-0.031*	-0.062*	0.056*	0.035*	0.026*		

* $p < 0.05$

Table 6 – Disentangling the Total Impact of Smartness on Customer Engagement and Customer Well-Being

PANEL A: The <i>total</i> impact (parameter estimates) of smartness on customer engagement: (i) direct effect plus (ii) indirect effects via the mediation of perceived personalization and perceived intrusiveness						
	Customer Engagement (CE) with Smart Product			Customer Engagement (CE) with Service Provider		
	Cognitive (CE _{d1})	Affective (CE _{d2})	Behavioral (CE _{d3})	Cognitive (CE _{d4})	Affective (CE _{d5})	Behavioral (CE _{d6})
Direct Effect						
Smartness (SMART) (β_{6d})	-0.097*	-0.131*	-0.108*	-0.225*	-0.148*	-0.195*
Indirect (Mediating) Effects						
Smartness through mediation of perceived personalization (SMARTxPP) ($\beta_{12x}\beta_{7d}$)	0.285*	0.219*	0.241*	0.128*	0.139*	0.148*
Smartness through mediation of perceived intrusiveness (SMARTxPI) ($\beta_{14x}\beta_{8d}$)	0.017*	-0.031*	-0.062*	0.056*	0.035*	0.026*
Total Effect (Population-Averaged) = Direct Effect + Indirect Effects						
Total effect of smartness on CE (direct and through the mediation of both perceived personalization and perceived intrusiveness) ($=\beta_{6d} + (\beta_{12x}\beta_{7d}) + (\beta_{14x}\beta_{8d})$)	0.205*	0.058*	0.071*	-0.041	0.025	-0.021
PANEL B: The <i>total</i> impact (parameter estimates) of smartness on customer engagement taking moderators into consideration: (i) direct effect plus (ii) indirect effects via the mediation of perceived personalization and perceived intrusiveness, and (iii) also accounting for the moderating influence of need for personalization and intrusiveness sensitivity ¹						
	Customer Engagement (CE) with Smart Product			Customer Engagement (CE) with Service Provider		
	Cognitive (CE _{d1})	Affective (CE _{d2})	Behavioral (CE _{d3})	Cognitive (CE _{d4})	Affective (CE _{d5})	Behavioral (CE _{d6})
Total Effect accounting for Customers' NP and IS (4 situations ²)						
1. Low NP and low IS	0.199*	0.046	0.060*	-0.047	0.018	-0.025
2. High NP and low IS	0.258*	0.160*	0.171*	0.009	0.089*	0.014
3. Low NP and high IS	0.204*	0.038	0.044*	-0.032	0.027	-0.018
4. High NP and high IS	0.262*	0.152*	0.154*	0.024	0.098*	0.021
PANEL C: The <i>total</i> impact (parameter estimates) of smartness on customer well-being via the double mediation of (i) perceived personalization and perceived intrusiveness and (ii) customer engagement, (iii) thereby also accounting for the moderating influence of need for personalization and intrusiveness sensitivity¹						
	Customer Well-Being (CWB)					
	Self-Efficacy (CWB _{w1})			Technology Anxiety (CWB _{w2})		
Total Effect (through PP, PI and CE)	0,046*			-0.019		
Total Effect accounting for Customers' NP and IS (4 situations ²)						
1. Low NP and low IS	0,044*			-0,018		
2. High NP and low IS	0,070*			-0,026 ^A		
3. Low NP and high IS	0,039*			-0,011		
4. High NP and high IS	0,064*			-0,019		

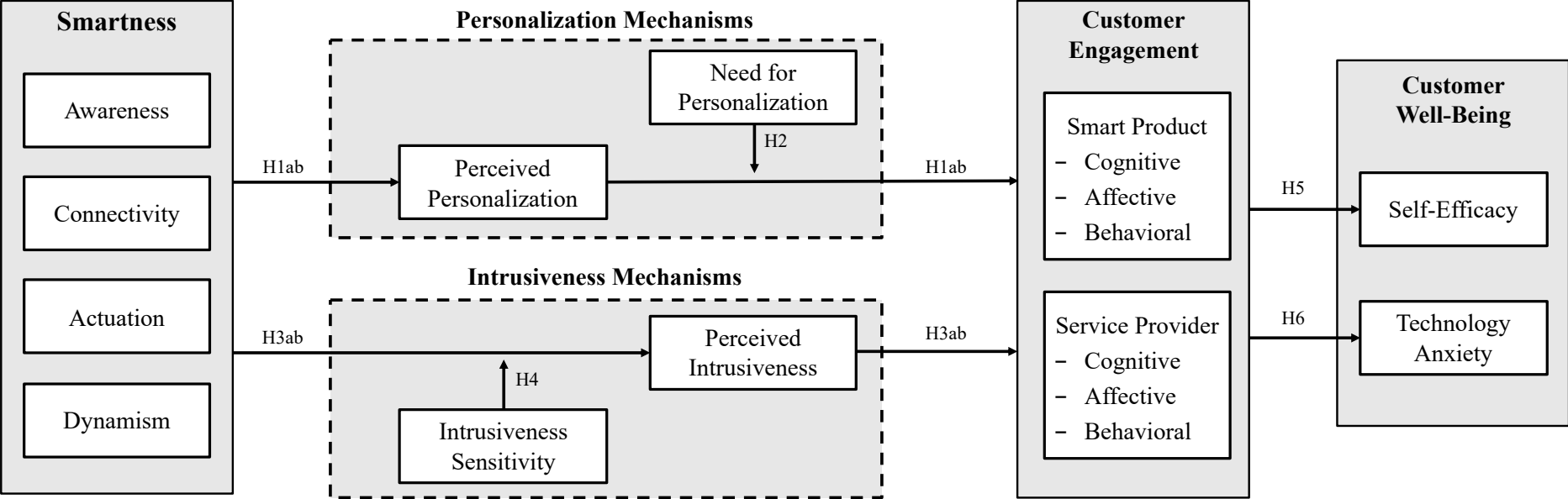
* $p < 0.05$; ^A Marginally Significant at $p = 0.078$

Note. CE = customer engagement; NP = need for personalization; IS = intrusiveness sensitivity;

¹ note that neither the direct impact of IS, nor the direct impact of NP on CE are accounted for in this table as the focus here is on the moderating influence of both NP and IS on the smartness–engagement relationship.

² For “low” the Q1 (i.e., first quartile) values for NP and IS are used, whereas for “high” the Q3 (i.e., third quartile) values are used.

Figure 1 – Conceptual Model



Note. H1b and H3b hypothesize about the strength of the mediating effect on customer engagement with the smart product relative to customer engagement the service provider

APPENDIX. Constructs and Confirmatory Factor Analyses

	Exploratory Study	Main Study
	Factor loading ¹	Factor loading ¹
Smartness Characteristics (adapted from Rijdsdijk et al., 2007; Rijdsdijk & Hultink, 2009)		
<i>Awareness</i> ($CR = 0.97$; $AVE = 0.91$; $Cr.\alpha = 0.968$)		
1. This smart fridge keeps an eye on itself and its environment.	0.950	0.876
2. This smart fridge is aware of itself and its environment.	0.938	0.827
3. This smart fridge observes itself and its environment.	0.974	0.910
<i>Connectivity</i> ($CR = 0.97$; $AVE = 0.88$; $Cr.\alpha = 0.968$)		
1. This smart fridge is connected to different actors.	0.944	0.902
2. This smart fridge can communicate with different actors.	0.977	0.930
3. This smart fridge can cooperate with different actors.	0.958	0.929
4. This smart fridge is attached to different actors.	0.880	0.813
<i>Actuation</i> ($CR = 0.95$; $AVE = 0.82$; $Cr.\alpha = 0.949$)		
1. This smart fridge can take initiative.	0.921	0.864
2. This smart fridge can work independently.	0.925	0.864
3. This smart fridge can go its own way.	0.873	0.781
4. This smart fridge can do things by itself.	0.909	0.835
<i>Dynamism</i> ($CR = 0.97$; $AVE = 0.90$; $Cr.\alpha = 0.971$)		
1. This smart fridge takes previous collected information into account to make decisions.	0.901	0.822
2. This smart fridge can learn.	0.945	0.938
3. This smart fridge can improve itself.	0.975	0.930
4. This smart fridge will be able to deliver a better performance over time.	0.968	0.919
Customer Engagement (adapted from Hollebeek et al., 2014)		
Using these services would ...		
<i>Cognitive dimension with smart product/service provider</i> ($CR = 0.88/0.87$; $AVE = 0.71/0.60$; $Cr.\alpha = 0.875/0.861$)		
... get me to think about the smart fridge/grocery store.		0.851/0.786
... make me think a lot about the smart fridge/grocery store.		0.883/0.885
... stimulate my interest to learn more about the smart fridge/grocery store.		0.791/0.817
<i>Affective dimension with smart product/service provider</i> ($CR = 0.94/0.94$; $AVE = 0.84/0.83$; $Cr.\alpha = 0.940/0.937$)		
... make me feel very positive about the smart fridge/grocery store.		0.896/0.889
... make me happy about the smart fridge/grocery store.		0.938/0.919
... make me feel good about the smart fridge/grocery store.		0.915/0.932
<i>Behavioral dimension with smart product/service provider</i> ($CR = 0.90/0.81$; $AVE = 0.81/0.68$; $Cr.\alpha = 0.894/0.807$)		
... make me to continue using the smart fridge/grocery store.		0.885/0.776
... make me recommend the smart fridge to other people/grocery store.		0.917/0.876

¹ Factor loading extracted from CFA

APPENDIX. Constructs and Confirmatory Factor Analyses – Continued

	Exploratory Study	Main Study
	Factor loading ¹	Factor loading ¹
Personalization Mechanisms (adapted from Xu et al., 2011)		
<i>Perceived personalization</i> ($CR = 0.92$; $AVE = 0.75$; $Cr.\alpha = 0.920$)		
The smart fridge/service is able to provide me with...		
1. ... personalized services.		0.913
2. ... services that are tailored to my needs.		0.926
3. ... more relevant services that are tailored to my preferences or personal interests.		0.890
4. ... the kind of services that I might like.		0.730
<i>Need for personalization</i> ($CR = 0.94$; $AVE = 0.79$; $Cr.\alpha = 0.938$)		
Overall, I like to get ...		
1. ... personalized services/products.		0.885
2. ... services/products that are tailored to my needs.		0.918
3. ... services/products that are tailored to my preferences or personal interests.		0.916
4. ... services/products that provide me with the kind of offers that I might like.		0.842
Intrusiveness Mechanisms (adapted from Edwards et al., 2002)		
<i>Perceived Intrusiveness</i> ($CR = 0.96$; $AVE = 0.83$; $Cr.\alpha = 0.959$)		
The smart fridge/service is able to ...		
1. ... interfere in my life.		0.859
2. ... intrude my life.		0.944
3. ... invade my life.		0.955
4. ... force itself into my life.		0.881
5. ... be obtrusive.		0.901
<i>Intrusiveness sensitivity</i> ($CR = 0.97$; $AVE = 0.86$; $Cr.\alpha = 0.969$)		
Overall, I am concerned about services/products ...		
1. ... interfering in my life.		0.910
2. ... intruding into my life.		0.935
3. ... invading my life.		0.947
4. ... forcing themselves into my life.		0.919
5. ... being obtrusive.		0.933
Customer Well-Being (adapted from Mani & Chouk, 2018; Meuter et al., 2005)		
<i>Self-efficacy</i> (adapted from Meuter et al., 2005)		
($CR = 0.85$; $AVE = 0.74$; $Cr.\alpha = 0.848$)		
1. I am fully capable of using smart services.		0.812
2. I am confident in my ability to use smart services.		0.907
<i>Technology anxiety</i> (adapted from Mani & Chouk, 2018; Meuter et al., 2005)		
($CR = 0.92$; $AVE = 0.79$; $Cr.\alpha = 0.919$)		
1. I have avoided technology because it is unfamiliar to me.		0.886
2. I hesitate to use most forms of technology for fear of making mistakes I cannot correct.		0.893
3. I feel apprehensive about using technology.		0.892

¹ Factor loading extracted from CFA