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WHAT DRIVES CONSUMERS' TRUST IN PROACTIVE SERVICES: A BEST-WORST SCALING APPROACH

Research in Progress

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Abstract

Increasing advancements in digital technologies, especially in artificial intelligence, are changing the nature of services. Services no longer rely on the consumers making the first move, but instead, service providers can anticipate consumers' needs and address them proactively by so-called proactive services (PAS). Within this new service type, consumers may enable the service provider to decide upon the consideration, decision, and enactment of the service. In PAS, consumers assign these previously "owned" phases to the service provider and thereby, also devolve power to the provider. Thus, trust is an indisputable prerequisite for consumer acceptance. However, it is unclear how individual characteristics of PAS impact consumers' trust. Addressing this research gap, this research-in-progress paper proposes a Best-Worst scaling survey in which potential consumers of two exemplary PAS state their trust with respect to different PAS characteristics. Thereby, this paper will extend the knowledge in understanding PAS.

Keywords: Proactive Services, Explorative Study, Trust, Best-Worst scaling.

1 Introduction

In the digital age, the nature of services is changing. Service providers become more and more familiar with emerging digital technologies such as artificial intelligence (AI) which enable them to make full use of their consumers' data (Barrett et al., 2015; Medina-Borja, 2015; Setia et al., 2013). By their means, service providers can now reasonably grasp their consumers' behavior, needs, and wishes – even on an individual level – which enables highly personalized services (Chen and Popovich, 2003; Froehle and Roth, 2004; Hennig-Thurau et al., 2010; Larivière et al., 2017). Overall, a technology- and data-driven paradigm shift is taking place in the way service providers interact with consumers to offer them highly personalized services that address their needs (Dauda and Lee, 2015). In line with this development, novel forms of services evolve with proactive services (PAS) at the forefront (Rau et al., 2020).

PAS do not involve a traditional demand setting, in which the service provider waits for the consumers' inquiry ("pull"-rationale), but instead, they continuously analyze consumers' activities and pre-emptively act ("push"-rationale). Leyer et al. (2017) conceptualize PAS by introducing this "push"-rationale which contrasts with the traditional "pull"-rationale. Making use of personal and contextual data from heterogeneous sources by advanced digital technologies (Hammer et al., 2015; Lee et al., 2011; Leyer et al., 2017), PAS anticipate consumers' needs, provide consumers with decision support, assist in the execution of decisions or actions, or even decide and act on behalf of consumers.

In practice, PAS are increasingly available and in use. Especially in the business-to-business (B2B) context, PAS like predictive maintenance are already present (e.g., Artesis, 2021; NS Energy, 2019). In contrast to traditional maintenance services, there are no fixed scheduled intervals for maintenance as services depend on AI-supported predictions of errors to reduce maintenance effort while minimizing downtimes (Wang et al., 2007). In the business-to-consumer (B2C) context, PAS with a high level of autonomy (e.g., deciding on behalf of consumers) are still on the path to materialize (Rau et al., 2020), yet PAS on a low level of maturity exists in practice (e.g., online comparison portals with proactive insurance rate recommendations). Thus, PAS are on the verge of fully accessing and arriving in the B2C context but as of now, only a few publications deal with PAS in a B2C context (Rau et al., 2020). Since practice is ahead of research, we as IS research community need to investigate this topic urgently.

Till now, the existing body of knowledge already includes studies focusing on the transformation to (Kowalkiewicz et al., 2016) and specification of (Woerndl et al., 2011) PAS, yet consumers' acceptance of PAS is still to be researched in more detail (Leyer et al., 2017). As the use of PAS goes along with conceding phases of service provision (i.e., consideration, decision, and enactment) and thus, devoting power to the service provider, trust is an indisputable prerequisite for accepting PAS (Leyer et al., 2017). While trust is a well-researched topic in service science and IS research (e.g., Bayer et al., 2021; Chasin et al., 2019; Taddeo and Floridi, 2011; Toreini et al., 2020), PAS exhibit unique characteristics (Rau et al., 2020) that even motivate reconceptualizing trust (Rosemann, 2021). Answering the corresponding call for further research (e.g., Rau et al., 2020), we examine the following research question.

How does the interplay of individual characteristics of PAS impact consumers' trust in them?

Presenting a research-in-progress paper, we start answering this question by differentiating PAS from digital and smart services as well as presenting their unique characteristics by the means of Rau et al.'s (2020) taxonomy. In section two, we further provide the theoretical background for trust in PAS. In section three, we outline the research method featuring a Best-Worst scaling approach. In the ensuing section, we present the expected results while emphasizing the contribution. We conclude in section 5 by discussing limitations and proposing suggestions for further research.

2 Theoretical Background

Service science is an inherently interdisciplinary field and thus, there are multiple conceptualizations and understanding of services, yet no generally accepted definition (Alter, 2012; Rai and Sambamurthy, 2006; Spohrer and Maglio, 2010). However, most scholars (e.g., Peters et al., 2016; Vargo and Lusch, 2016) agree that services involve at least two entities with different roles (e.g., service provider and consumer) which use and integrate resources in an interactive and collaborative process to co-create value for mutual benefit. Enhanced by the ongoing digitalization many different types of services arose. At its forefront are PAS which have great economic potential yet also issues like trust to overcome (Leyer et al., 2017). To understand PAS and trust as their major requirement, we illustrate the corresponding academic discourse in the remains of this section.

2.1 Proactive Services

To understand PAS and its distinction within service science, we seek to identify characteristics that PAS inherit from related service types such as digital or smart services, but also characteristics that make PAS unique. Digital services exclusively exist and operate in a digital environment featuring digital transactions and thus, enable the collection and analysis of data (Beverungen et al., 2019; Lovelock and Gummesson, 2004; Vargo and Lusch, 2008; Williams et al., 2008). Due to advances in IT in recent years, the concept of digital services evolved, which in turn has given rise to smart services (Barrett et al., 2015; Rau et al., 2020). Their "smartness" refers to the capabilities to make use of those data by AI, on the one hand, and on the other hand to the inclusion of smart things (Alter, 2020; Barile and Polese, 2010; Beverungen et al., 2019; Ouyang et al., 2016; Wünderlich et al., 2015). According to Lim and Maglio (2018), a smart service defines a service capable of learning, dynamic adaptation, and decision-making that involves smart things. Thus, in summary, digital and smart services have the following characteristics in common with PAS: digital transactions, the use of smart things (optional), the analysis of data to predict consumer's needs, and the adaptation to changing consumer and situational conditions (Rau et al., 2020). Complementary, there are further characteristics distinguishing PAS from digital and smart services. A central aspect of PAS is the anticipation of consumers' needs even before the consumers might know them themselves and unlike traditional service models, PAS always act proactively in regard to the moment the value proposition is offered (Rau et al., 2020). In the case of a smart fridge, for example, the identification of an upcoming birthday could be the trigger to order a cake before the customer has even identified this need. The "push"-rationale is therefore a central characteristic of PAS. In respect to the degree of autonomy, however, Rau et al. (2020) and Leyer et al. (2017) distinguish the following three stages of customer relief of PAS: PAS seamlessly provide decision support (*recommender* – smart fridge proposes three different cakes), assist in the execution of a decision (*assistant* – smart fridge puts a cake in the online shopping cart), or even decide and act on behalf of the consumer (*autopilot* – smart fridge buys a cake). Accordingly, PAS might no longer wait for a consumers' inquiry as in a traditional demand setting but rather make the first move and allow for a pre-emptive (inter)action (Rau et al., 2020). Since services deliveries, though, are traditionally consumer-initiated service delivery (i.e., *"pull"-rationale*) and PAS are business-initiated services (i.e., "*push"-rationale*) this is a substantial paradigm shift in service science (Hammer et al., 2015; Lee et al., 2011; Leyer et al., 2017). It is no longer necessary for customers to develop needs and then "pull" a corresponding service; instead, the initiative shifts to PAS, which "push" a service to customers based on the anticipation of needs through the analysis of large amounts of data via digital technologies.

The functioning of PAS strongly relies on advanced data analysis capabilities, large amounts of data from heterogeneous sources, and an increased willingness on part of the consumers to disclose personal data (Kowalkiewicz et al., 2016; Medina-Borja, 2015; Setia et al., 2013). PAS collect large amounts of personal (e.g., consumers' goals, preferences, processes, daily routines) as well as contextual data (e.g., weather, location), which they continuously analyze to identify trigger events for a proactive offer (Leyer et al., 2017). Additionally, PAS vary from smart and digital services by setting up a comprehensive consumer model based on the heterogeneous data collected (Chen and Popovich, 2003). As consumers' goals, preferences, and processes are dynamic, PAS continuously update their consumer models and anticipate consumers' behavior from past interactions and spontaneous behavioral changes (Chen and Popovich, 2003). Combined with advanced analytical methods (e.g., machine learning) and self-x capabilities, PAS result in a high degree of individualization for consumers. In sum, the distinctive characteristic of PAS unfold in the interplay of the following three areas: consumer (e.g., profiling of consumers' behavior and preferences as well as a shift to autonomous behavior with no consumer involvement), data (e.g., the anticipation of consumer needs based on the analysis of a diverse set of data), and interaction (e.g., "push"-rationale) (Rau et al., 2020). Consequently, PAS differ significantly from related services such as *smart (interactive) services* (Beverungen et al., 2019; Wünderlich et al., 2013; Wünderlich et al., 2015) as PAS do not require yet can include human to human interaction as well as intelligent objects and different degrees of the degree of autonomy. Analogously, PAS distinguish from *separate services* (e.g., Keh and Pang, 2010) and *remote services* (e.g., Paluch and Blut, 2013) by the "push"-rationale, the central characteristic of PAS.

To conceptualize PAS, Rau et al. (2020) develop a multi-layer taxonomy visualized in Figure 1. It comprises nine dimensions and 23 characteristics with plenty of interesting highlights of which we emphasize the most relevant for this paper in the following. We thus kindly ask you to refer to Rau et al. (2020) for further details. For this paper, the dimension of *customer belief* is particularly interesting since it specifies the activities from which the PAS relieves the consumer – the main driver for the raised paradigm shift. PAS can relieve customers in three phases: the consideration phase (i.e., PAS provides decision support), the decision phase (i.e., PAS decides on behalf of the customer), and the enactment phase (i.e., PAS assists in the decision execution). *Customer Benefit* specifies the value proposition (e.g., time and money savings). In contrast, *Customer Risk* specifies the involved risk depending on the domain and the individual task the PAS performs. They are two sides of the same coin meaning that greater risk usually corresponds to greater benefit and vice versa. Analogously, including personal (e.g., preferences, goals, activities) and/or contextual (e.g., weather, product availability) data as compromised in *Data Source* may lead to greater benefit, yet requires the consumers to reveal more of themselves.

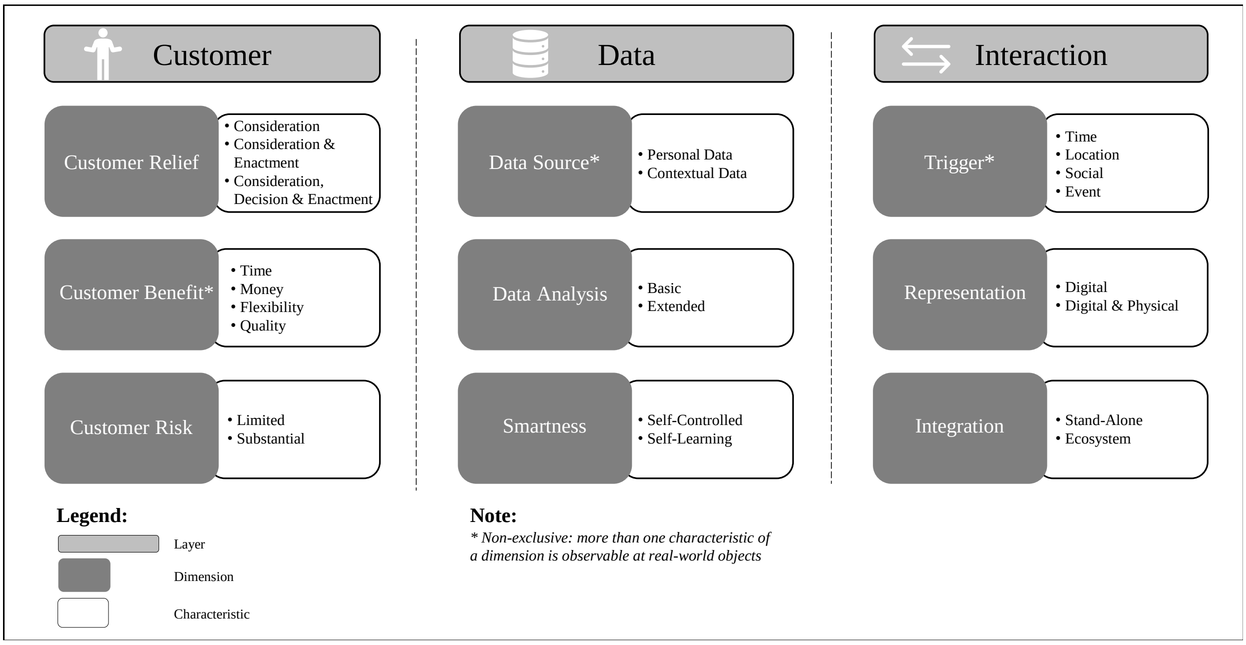


Figure 1. Taxonomy of PAS (Rau et al., 2020).

Besides technical challenges, for successful PAS further obstacles are yet to be overcome. Its greatest one is simultaneously its greatest benefit as we illustrate in the following. For effective use of PAS, the consumer provides – depending on the Customer Relief – information like preference in nutrition, living habits, or even credit card information. Furthermore, this goes along with a perceived risk increase for the consumers considering that they might not be involved in all phases of the service provision anymore (i.e., consideration, decision, and enactment). By this, the consumer devotes power to the service provider allowing it to manage previously owned phases in the traditional service provision. In general, intentionally devoting power requires trust (Luhmann, 2017). Previous research (Leyer et al., 2017) has provided evidence for its maintaining validity in the area of PAS showing that trust is an indisputable antecedent for the consumers' willingness to accept PAS.

2.2 Trust in Proactive Services

Trust is certainly a well-researched concept, but there is still a lack of a shared understanding. Even within IS research definitions and conceptualizations of trust are manifold (Gefen et al., 2003; McKnight et al., 2002; Shapiro, 1987). However, the *ability, benevolence, and integrity (ABI) framework* has emerged as a predominant conceptualization of trust, especially when assessing trust in technologies (e.g., Bayer et al., 2021; Benbasat and Wang, 2005; Gefen et al., 2003; Li et al., 2008; McKnight et al., 2002). *Ability* refers to the trustor's – in the case of PAS: the consumer – perception that a trustee – the PAS – has the skills and competence to perform effectively in the specific trusting domain. *Benevolence* is the trustor's perception that the trustee acts in the trustor's best interest. *Integrity* is the perception that the trustee adheres to a set of principles (e.g., honesty) generally accepted by the trustor.

Even though the *ABI framework* is well-established in the IS literature for conceptualizing trust, it is rarely applied in professional practice (Rosemann, 2021). In addition, conceptualizations of trust are primarily based on concepts from a pre-digital world making it reasonable to question their validity for digital contexts (Rosemann, 2021), especially when considering the latest developments that even lead to paradigm shifts such as PAS within service science. For this reason, Rosemann (2021) proposes a new conceptualization of trust featuring *core trust* and *extreme trust*. *Core trust* refers to the expectation of the trustor that the trustee can deliver to its promise – in one single word reliability. Complementary, *extreme trust* refers to the principle that a trustor trusts the trustee more than themselves. In the context of PAS such as a smart fridge, this represents a situation in which the consumer hands over private data, lets the smart fridge proactively generate a shopping list and buy on behalf of the consumer, but still expects a seamless execution of all related processes (Rosemann, 2021). Thus, especially extreme trust seems to adapt to the conceptual changes that go along with PAS.

Since PAS is one of the most recent developments within the domain of service science, little research exists, especially regarding consumers' trust in PAS (Leyer et al., 2017; Rau et al., 2020). However, some studies investigate consumers' trust in digital and smart services functionally relate to PAS. Concerning digital services such as recommender systems, Benbasat and Wang (2005) were the first to confirm the nomological validity of trust in digital services by integrating trust in the Technology Acceptance Model by Davis et al. (1989). Furthermore, Wang and Benbasat (2016) investigate the different influences of two sets of experiential reasons on the *ABI Framework* in recommender systems. As a result, they reveal different antecedents of the *ABI Framework* and provide guidelines for designers to choose specific design elements to improve a particular ABI component. Analogously thereto, this paper examines the effects of PAS characteristics on customers' trust as a highly relevant research topic. Even though trust in services has been researched for a while, PAS differ significantly from related service concepts by its functionality, the push-rationale. Therefore, there is a call for specific research upon trust in PAS (e.g., Rau et al., 2020; Rosemann, 2021) addressed in this research paper.

3 Research Method

This is a research-in-progress proposing an online survey yet to conduct. We plan to achieve a balanced sample of PAS users in terms of gender, education, income, and family status through careful channel selection and to reach at least 300 respondents with the survey as in alike studies (e.g., Lansing et al., 2019; Schmidt-Kraeplin et al., 2020).

For empirical surveys, there are several suitable techniques in academia such as simple ranking mechanisms, rating scales (e.g., Likert scales), conjoint analysis, or maximum difference scaling (MaxDiff) (Schöbel et al., 2016). Investigating the impact of individual PAS characteristics on consumers' trust, we adhere to fellow IS scholars (e.g., Lansing et al., 2019; Schmidt-Kraeplin et al., 2020) investigating respondents' preferences for a set of objects and choose the Best-Worst scaling (BWS). BWS applies the MaxDiff approach (Louviere et al., 2013; Schmidt-Kraeplin et al., 2020) by making the respondents repeatedly choose between two objects with the greatest perceptual difference on an underlying continuum of interest among three or more objects, the choice set (Finn and Louviere, 1992). This procedure offers four great advances. First, by the enforced trade-offs, the respondent must – unlike in rating-scaled approaches – discriminate between objects and cannot rate each object equally important (Louviere et al., 2013). Second, the approach is scale-independent and therefore, does not suffer from potential order effects or response biases (Lee et al., 2013; Schmidt-Kraeplin et al., 2020). Third, each selection of a pair of objects also implicitly provides information for the unselected attributes which enriches the ranking information (Marley and Louviere, 2005). Fourth, it enables to survey valid and realistic combinations of features and thus, prevents unrealistic yet desired combinations such as providing no personal data but longing for personalized offers. In conclusion, BWS provides robust statistical comparisons between respondents and is less prone to indecisiveness regarding the discrimination of objects in comparison to other preference elicitation methods like rating scales. In the remainder of this section, we illustrate the design of the survey including the BWS.

3.1 Best-Worst Scaling

For the PAS characteristics in this survey, we stick to the taxonomy of Rau et al. (2020) structured as several dimensions (e.g., Consumer Benefit) with several different characteristics (e.g., Time, Budget) each. Regarding every dimension on its own, it is apparent which characteristics lead to greater trust: Personal or contextual data? Limited or substantial consumer risk? Little or much money savings? However, these characteristics are not mutually independent and so, substantial consumer risk, for example, will probably lead to greater savings. Consequently, a choice between different PAS configurations is a cost-benefit consideration and thus, only an integrated view on the dimensions is suitable for meaningful implications. With this in mind, we chose multi-profile BWS as respondents select the best and worst among complete profiles consisting of several dimensions that differ by their characteristics. Furthermore, in contrast to object-case and profile-case BWS, multi-profile -case BWS enables to have a different number of characteristics for each dimension (Marley and Louviere, 2005). This is highly advantageous when considering that Customer Benefit, for example, has four, yet, Data Source only has two different characteristics.

For the BWS, we favor a between-subject design with two different PAS which will – in contrast to one PAS – enable the conclusion on more generalizable findings. For one the PAS, we adhere to previous research (Rau et al., 2020) and refer to a smart fridge. Smart fridges are becoming more familiar in public as an established PAS and by this, they assist the respondents in the survey by simplifying to picture using a PAS. For the other PAS, we comply with the B2C market mirroring the service by Stich Fix (2021), a fully automated clothing delivery service provider. To verify the dimensions of PAS for our research objective, we established two criteria to determine the relevant dimensions for the PAS profiles and are going to validate them with 10 experienced HCI researchers. First, a change of its specification does not affect the PAS core (exclusion of *Representation* as a smart fridge for instance will always contain a physical and digital component and *Integration* refers to the context of the PAS). Second, the dimension must be easily perceptual for the consumer meaning that a change of its specification cannot remain unnoticed in the interaction with the PAS (exclusion of *Data Analysis* and *Smartness* – simple correlation vs. deep neuronal networks with continuous learning). As a result, we focus on the following dimensions: *customer relief, customer benefit, customer risk, data source,* and *trigger*.

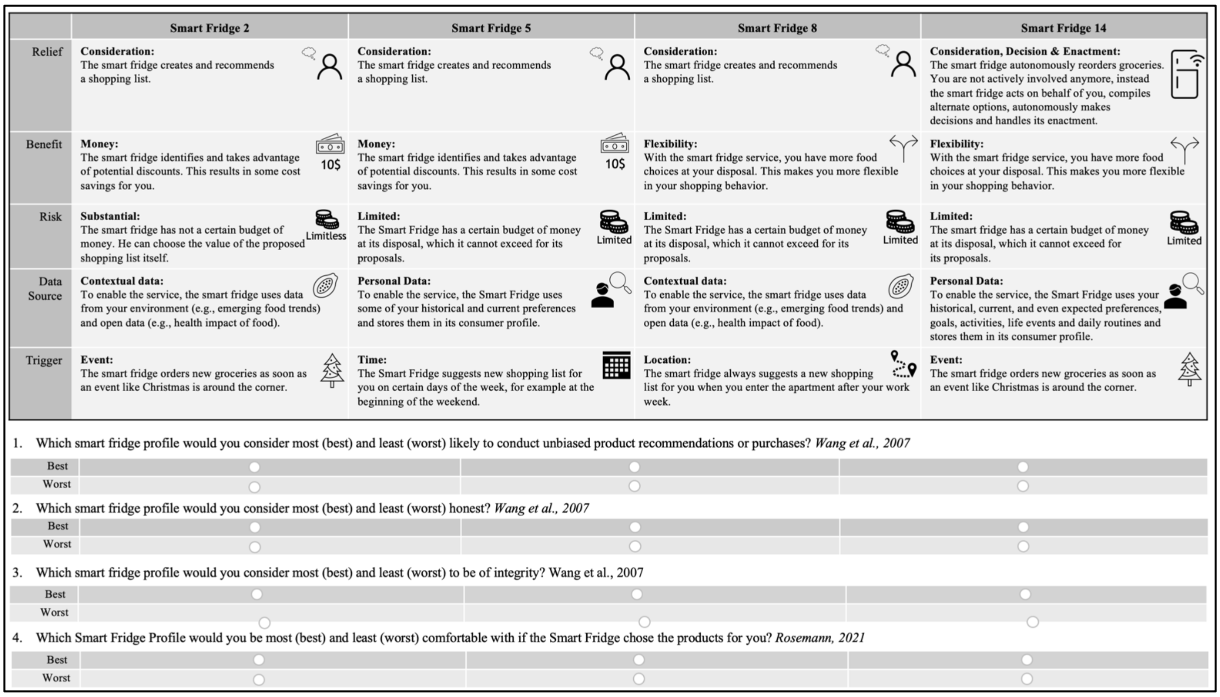
3.2 Survey Procedure

To structure the survey, we replicated the procedure of Schöbel et al. (2016) and Schmidt-Kraepelin et al. (2020) favoring a three-step procedure – first, introduction to the survey, the context and description of PAS dimensions and characteristics, second, attention checks and BWS choice task, and third, collection of demographic information. In advance of the survey, we counteracted potential errors and incomprehensibility in the survey, by introducing it to 10 experienced HCI survey researchers. We incorporated their feedback into the final survey represented in the remains of this section.

First, we make the respondents imagine that they either own a smart fridge or are a customer of an automated clothing delivery service that aims to facilitate weekly grocery or clothing shopping by suggesting groceries or clothing, handling payment processing, or even ordering autonomously based on their goals, preferences, and needs. Subsequently, we describe the different dimensions and characteristics of PAS in the context of a smart fridge or automated clothing delivery service and visualize each characteristic with an icon to facilitate information processing for the respondents. To ensure that respondents read and understood the various PAS dimensions and characteristics in the context of a smart fridge or an automated clothing delivery service, we add two comprehension questions related to *customer relief* and *data source* as attention checks. For the ensuing analysis, we will only consider the data of respondents answering both questions correctly. To further reduce potential misunderstandings, we explain the meaning of special terms (i.e., unbiased, honest, integrity) used in the ensuing BWS in the context of PAS.

Second, we will conduct the BWS adhering to previous scholars (e.g., Flynn et al., 2007; Lansing et al., 2013; Louviere et al., 2013; Severin et al., 2013). Analogously, we developed the PAS profiles and assigned the profiles to the choice sets using an orthogonal main effects plan and a balanced incomplete block design according to Louviere et al. (2015, see Table 4.2/4.4 on p. 92/93 for the exact illustration). Applying this experimental design ensures that each option – in this case, a smart fridge profile, for example, as in Figure 2 – appears and co-appears equally often with each other option (Lee et al., 2008; Louviere et al., 2013). As a result, we show each respondent 20 different choice sets with a total of 16 different PAS profiles. Each choice set consists of four different PAS profiles and each profile occurs five times and is compared once to every other PAS profile (Louviere et al., 2015). Among a PAS dimension, the characteristics appear equally often in PAS profiles despite for Customer Relief dimension. Since it has three different characteristics, it is mathematically impossible to distribute them equally over 16 profiles. For this reason, the *consideration* characteristic appears twice as often in the

PAS profiles as consideration & enactment and consideration, decision, and enactment. For measuring trust, we favor a multi-pronged approach adopting versions of the newly proposed *extreme trust* by Rosemann (2021) as well as the well-established *trusting beliefs* utilized in various IS Papers (e.g., Bayer et al., 2021; Wang and Benbasat, 2007). By this procedure, we ensure scientific validity, yet also proceed innovatively, gaining insight about a rather new trust construct specified for the digital world. Please refer to Figure 2 for the designed items.



	Smart Fridge 2	Smart Fridge 5	Smart Fridge 8	Smart Fridge 14
Relief	**Consideration:** The smart fridge creates and recommends a shopping list.	**Consideration:** The smart fridge creates and recommends a shopping list.	**Consideration:** The smart fridge creates and recommends a shopping list.	**Consideration, Decision & Enactment:** The smart fridge autonomously reorders groceries. You are not actively involved anymore, instead the smart fridge acts on behalf of you, compiles alternate options, autonomously makes decisions and handles its enactment.
Benefit	**Money:** The smart fridge identifies and takes advantage of potential discounts. This results in some cost savings for you. 10$	**Money:** The smart fridge identifies and takes advantage of potential discounts. This results in some cost savings for you. 10$	**Flexibility:** With the smart fridge service, you have more food choices at your disposal. This makes you more flexible in your shopping behavior.	**Flexibility:** With the smart fridge service, you have more food choices at your disposal. This makes you more flexible in your shopping behavior.
Risk	**Substantial:** The smart fridge has not a certain budget of money. He can choose the value of the proposed shopping list itself. Limitless	**Limited:** The Smart Fridge has a certain budget of money at its disposal, which it cannot exceed for its proposals. Limited	**Limited:** The Smart Fridge has a certain budget of money at its disposal, which it cannot exceed for its proposals. Limited	**Limited:** The smart fridge has a certain budget of money at its disposal, which it cannot exceed for its proposals. Limited
Data Source	**Contextual data:** To enable the service, the smart fridge uses data from your environment (e.g., emerging food trends) and open data (e.g., health impact of food).	**Personal Data:** To enable the service, the Smart Fridge uses some of your historical and current preferences and stores them in its consumer profile.	**Contextual data:** To enable the service, the smart fridge uses data from your environment (e.g., emerging food trends) and open data (e.g., health impact of food).	**Personal Data:** To enable the service, the Smart Fridge uses your historical, current, and even expected preferences, goals, activities, life events and daily routines and stores them in its consumer profile.
Trigger	**Event:** The smart fridge orders new groceries as soon as an event like Christmas is around the corner.	**Time:** The Smart Fridge suggests new shopping list for you on certain days of the week, for example at the beginning of the weekend.	**Location:** The smart fridge always suggests a new shopping list for you when you enter the apartment after your work week.	**Event:** The smart fridge orders new groceries as soon as an event like Christmas is around the corner.

1. Which smart fridge profile would you consider most (best) and least (worst) likely to conduct unbiased product recommendations or purchases? *Wang et al., 2007*
Best
Worst
2. Which smart fridge profile would you consider most (best) and least (worst) honest? *Wang et al., 2007*
Best
Worst
3. Which smart fridge profile would you consider most (best) and least (worst) to be of integrity? Wang et al., 2007
Best
Worst
4. Which Smart Fridge Profile would you be most (best) and least (worst) comfortable with if the Smart Fridge chose the products for you? *Rosemann, 2021*
Best
Worst

Figure 2. An example of a BWS choice set.

Third, besides basic demographic information (i.e., gender, age, family status, educational level, monthly net income), we also adopt scales for constructs providing insights about the general individual attitude of the participants potentially affecting our results. For this, research in related areas such as smart home services (Schomakers et al., 2021) provides evidence that for consumers' preferences, there is an interplay between trust, *affinity for technology interaction* (Franke et al., 2019), and *privacy concerns* (Xu et al., 2011). On top, we survey the preferences in terms of nutrition (Chandon and Wansink, 2007) as well as shopping (Vohs et al., 2014).

4 Outlook and Expected Contribution

This research-in-progress paper describes the theoretical basis, design, and envisaged data analysis of a BWS approach aiming to examine how the interplay of PAS characteristics affects consumers' trust in PAS. At the current state, we have fully prepared the survey from a theoretical point of view. The next steps include conducting the survey, gathering and analyzing the empirical data. As BWS allows us to compare the impact of a single or a set of attributes (here: PAS characteristics) in an element (here: PAS), we expect to identify how the characteristics interact and which characteristics or rather combination of characteristics drive and affect consumers' trust in PAS. By this, we contribute twofold.

First, a great priority within service science is providing insight to successfully design new services using digital possibilities (Ostrom et al., 2015). We extend the existing body of knowledge by focusing on the new service type, PAS, enabled by the enhanced possibilities using AI. The study will provide new insights for developing PAS that consumers will trust. Consequently, since trust plays a significant role in the consumers' general acceptance of PAS (Leyer et al., 2017), consumers will more likely accept PAS they can trust. From a practical point of view, the results will simplify to prioritize PAS characteristics in terms of trust and thus, consumer acceptance. This will enable service providers to design PAS more successfully because they can check current configurations for trust issues or evaluate PAS configurations ex-ante and thus, save resources.

Second, trust is a well-established, yet still highly relevant research object, in service sciences and holistically in IS research as shown by multiple recent publications (e.g., Bayer et al., 2021; Lin et al., 2021; Rosemann, 2021; Toreini et al., 2020; Voorhees et al., 2021). Nonetheless, to the best of our knowledge, this research paper is the first response to the call (e.g., Rau et al., 2020) for examining trust in PAS. Furthermore, this study measures trust adhering to an established conceptualization of trust (i.e.: the ABI framework) as well as the newly introduced extreme trust destined for the digital world. Therefore, our expected results will provide interesting insights for a greater discourse about the conceptualization and implementation of trust within IS research and our digital world.

5 Conclusion

Advances in digital technologies and the increasing availability of data are leading to new service types, with PAS at the forefront. Addressing the accompanying paradigm shift of PAS, research pioneers postulate that the “push”-rationale is so unique that even a new conceptualization of trust, extreme trust, is necessary for PAS (Leyer et al., 2017; Rosemann, 2021). To account for the strong uptake of PAS in the industry in comparison to the IS research, we examine how individual characteristics of PAS affect consumers' trust based on the taxonomy of Rau et al. (2020) by the means of the proposed BWS.

However, as in every research endeavor, our research is subject to limitations that limit the explanatory power or even require further investigations. This includes the potential bias of two examples, the smart fridge and the automated clothing delivery service, – as in every online survey – the lack of control over the survey’s respondents’ surroundings, or the neglect of the communication between humans and PAS. Furthermore, we focus on the PAS characteristics, yet this does presumably not fully cover all aspects affecting trust in PAS. This might include characteristics of the service provider such as its reputation. Thus, we introduce fellow researchers to incorporate our results in a greater (e.g., company-wide) context to investigate how the PAS characteristics collude with other aspects. Nonetheless, this research-in-progress paper represents an important step contributing to a better understanding of PAS and provides new insights for further research in designing trusted, successful PAS.

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