Improving customer satisfaction in proactive service design

A Kano model approach

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Abstract

As an emergent variant of digital and smart services, proactive services (PAS) do not wait for customers to make the first move, but proactively participate in customers' lives and make decisions on their behalf. Due to their novelty, the literature on PAS is in its infancy. Specifically, there is a lack of guidance on designing PAS to meet customer needs. Hence, we examined how customers assess specific features of PAS and whether their assessments differ according to personality traits. To this end, we conducted an online survey via the crowdsourcing platform Prolific, which yielded 259 valid responses. We used a methodological combination of the Kano model, self-stated importance method, and the Five Factor model. Our results reveal that, at the moment, customers do not value features of PAS related to autonomy and that customers engage in paradoxical behavior when assessing the use of personal data. These results allow for a more precise classification and prioritization of the features of PAS tuned to a customer's most prevalent personality trait.

Keywords Customer satisfaction · Kano model · Proactive services · Personality traits · Service design

JEL classification M30 · O30 · L80 · L86

Introduction

Digitalization describes the increasingly intensive and rapid penetration of the economy and society with digital technologies as well as the associated changes with regard to

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the networking of individuals, organizations, and physical objects. Thereby, digital technologies make existing processes more efficient, enable new types of products and services, as well as new types of business models associated with opportunities concerning the interaction between customers and organizations (Gimpel & Röglinger, 2017; Shainesh, 2019). Today, customers can easily search for and compare information while selecting from a wide range of products and services and have access to services regardless of the time and location (Larivière et al., 2017; Shainesh, 2019). These new opportunities have also led to changes in customer expectations and attitudes. Customers expect personalized offers, simple purchase processes, and convenience (Latinovic & Chatterjee, 2019; Sharma et al., 2021). In return, they are increasingly willing to disclose personal data to receive value-adding services (Kowalkiewicz et al., 2016; Larivière et al., 2017). For service providers, this change brings both opportunities (e.g., improving customer experiences and increasing customer loyalty) and challenges (e.g., fast-changing customer needs) (Leimeister et al., 2014). Thus, more than ever, service providers must understand customers' unique problems and expectations, and the

context of those problems and expectations (Alt et al., 2019; Camp et al., 2018; Kreuzer et al., 2020). The new competitive environment increases the necessity to place customers at the center of all activities and to initiate service co-creation to deliver experiences that create value for customers and allow for meaningful connections between customers and service providers (Barrett et al., 2015; Kreuzer et al., 2020; Latinovic & Chatterjee, 2019).

This competitive environment has led to digital and smart services that are characterized by a proactive and autonomous nature, and thus called proactive services (PAS). On the one hand, digital technologies connect PAS with customers (e.g., via Internet-enabled mobile devices or smart things equipped with sensors and actuators) to continuously collect personal (e.g., goals, needs, and personality traits) and contextual data (e.g., geographical location, time, and activities) from diverse sources (e.g., explicit input from customers, implicit collection via mobile devices, and smart things). On the other hand, PAS also use these data to create individualized customer models. Based on insights derived from the customer model, PAS personalize their offerings to target customers' needs before customers are aware of them (Hammer et al., 2015; Leyer et al., 2017; Rau et al., 2020). PAS follow a "push-rationale" by anticipating customers' needs and providing decision support (i.e., recommending grocery purchases), assisting in the execution of decisions or actions (i.e., proposing a budget based on prior expenditures), or even deciding and acting on behalf of the customer (i.e., ordering groceries based on the current contents of the refrigerator) (Leyer et al., 2017; Rau et al., 2020). Depending on their exact manifestations, PAS have different degrees of autonomy and incorporate algorithmic decision-making.

Due to their novelty, little research is available on PAS or their design. One of the first studies was conducted by Woerndl et al. (2011), who developed and implemented a proactive gas station recommendation system. They based their model on contextual and personal attributes and investigated the correlation between proactive recommendations and customer assessments of proactive recommendation time. In another study, Kowalkiewicz et al. (2016) identified seven characteristics of proactive organizations and provided guidance on transforming into such an organization. Leyer et al. (2017) initially defined PAS and identified antecedents explaining the impact on customer acceptance of PAS. They based their acceptance model on the reasoned action approach and tested it via a scenario-based study in a university setting. Rau et al. (2020) developed a multi-layer taxonomy of the features of PAS and conducted an empirical assessment of PAS examples in the business-to-consumer context. With this PAS taxonomy, researchers and practitioners can describe, classify, analyze, identify, and cluster PAS based on their features. The taxonomy contributes to a better understanding of PAS. However, it provides little guidance

on designing PAS, as it lacks a prioritization of features from a customer perspective. PAS designs that target higher customer satisfaction (CSAT) can lead to greater economic success for service providers (Sureshchandar et al., 2002). Thus, we examined the following research question: *How do customers assess the features of PAS?*

To answer our research question, we based our research on Rau et al.'s (2020) taxonomy, which provides an overview of the features of PAS. Thereby, we designed an online survey with these features and used a methodological combination of the Kano model, self-stated importance method, and the Five Factor model (FFM) to assess customer perception of the features of PAS, to incorporate a prioritization of the features, and to determine the potential moderating effect of customer personality traits on CSAT (Kano et al., 1984; McCrae & Costa, 2004; Yang, 2005). The results allow for a more precise classification and prioritization of the features of PAS based on customers' primary personality traits. In particular, the incorporation of the FFM provided us with the additional benefit of being able to make clearer statements for up to 50% of the features that would otherwise be classified as indifferent. In this way, our research provides insights for service providers aiming to design PAS with high CSAT and can be seen as a blueprint for further conceptual developments of the Kano model.

Our paper is structured as follows: Second section provides a theoretical background on the features of PAS based on a taxonomy and the current literature regarding the influence of personality traits on CSAT. In the third section, we outline our methodological approach. In the fourth section, we present our results. First, we present the customers' general assessment of the features of PAS. Next, we present an assessment based on their personality traits. In the fifth section, we discuss the results and derive the theoretical and managerial implications. We conclude in the sixth section by discussing the limitations of the study and providing suggestions for future research.

Theoretical background

Proactive services

Rapid advancements in digital technologies and data analysis have changed the nature of services and have led to digital and smart services characterized by a proactive and autonomous nature (Alt, Demirkan, et al., 2019; Larivière et al., 2017; Leyer et al., 2017; Rau et al., 2020). According to these developments, these services are called proactive digital or proactive smart service or simply PAS (Rau et al., 2020). Thus, PAS are a subgroup of digital and smart services especially describing a proactive (e.g., push-rationale) and autonomous nature (Rau et al., 2020). PAS no longer
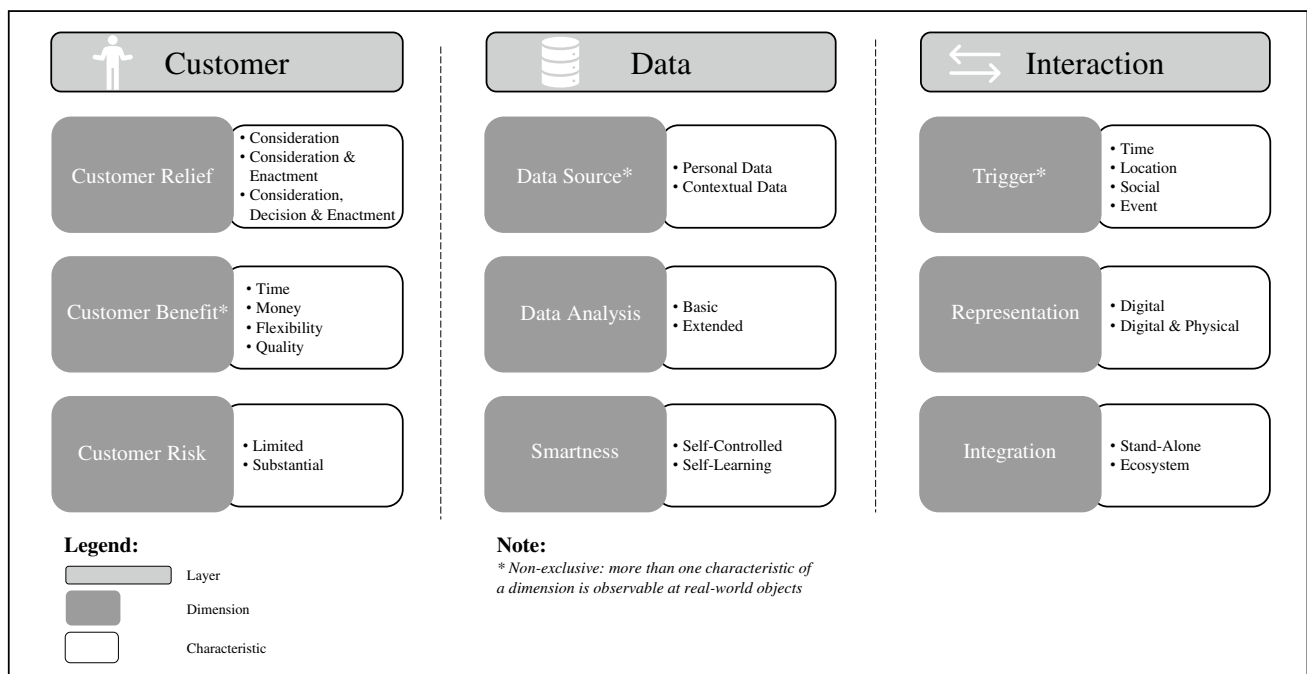
Fig. 1 Taxonomy of proactive services according to Rau et al. (2020)

wait for customers' inquiries but make the first move in customer interactions (Leyer et al., 2017). They can anticipate customers' needs and offer tailored offerings, even before the customers demand it (Leyer et al., 2017). This push-rationale is a constitutive feature of PAS that enables autonomous action on behalf of customers (Hammer et al., 2015; Lee et al., 2012). The functioning of PAS is based on heterogeneous data sources and data analysis capabilities. In this way, PAS identify and generate trigger events from personal (e.g., implicit and explicit goals, preferences, and activities) and contextual (e.g., weather, location) data. What is remarkable here is that personal data also includes customers' daily routines, and thus information from customers' daily processes (Bobadilla et al., 2013; Leyer et al., 2017; Ziefle et al., 2011). Based on these data, PAS exhibit a high degree of individualization and continuously update their internal models through learning and adaptation (Rau et al., 2020). To further enable customization, PAS also offer interaction capabilities (e.g., an opportunity for customer feedback) (Hammer et al., 2015; Leyer et al., 2017).

With regard to the autonomous nature of PAS, researchers, such as Leyer et al. (2017) and Rau et al. (2020), have classified PAS in three possible phases: (1) just-in-time decision support (i.e., pre-purchase stage with product recommendations, etc.), (2) decision on behalf of the customer (i.e., post-purchase stage with order handling, etc.), and (3) assistance in the execution of a decision (i.e., purchase stage with actual product selection and order placement, etc.). Therefore, PAS typically allow customers to configure the

underlying data sources, purpose of data usage, and scope (e.g., calendar management and grocery management) in each of the three phases mentioned above (Leyer et al., 2017; Rau et al., 2020). The most straightforward PAS archetype is a *recommender*, which, for instance, suggests buying a pair of shoes from an online shop based on the customer's shoe size, previous purchases, and preferences. In this example, the advanced PAS archetype *assistant* would support the customer in the execution (i.e., ordering, payment, and delivery) after the customer has decided to buy the suggested pair of shoes. In its most advanced archetype *autopilot*, the PAS also decides on behalf of the customer based on the analysis of the customer data model, which would include goals and preferences (e.g., deciding whether to buy a pair of shoes).

Beyond the differences concerning autonomy, Rau et al. (2020) analyzed PAS using a multi-layer taxonomy. Figure 1 visualizes this taxonomy, which differentiates characteristics of PAS. This taxonomy serves as the theoretical foundation of the present study. The Kano model was applied to obtain customer assessments of all characteristics of PAS. Below, we summarize the taxonomy dimensions to provide a reasonable understanding of the taxonomy used in our research approach. Please refer to Rau et al. (2020) for a detailed description of this taxonomy.

The multi-layer taxonomy consists of nine dimensions and 23 characteristics. The first layer, *customer*, describes features that directly affect the customer and comprises the dimensions of *customer relief*, *customer benefit*, and *customer risk*. *Customer relief* determines the activities from

which customers are relieved through the PAS. This relief relates to three degrees of PAS autonomy. In the lowest degree of autonomy (i.e., *customer relief*: Consideration), the PAS only informs the customer, but does not take any action itself (e.g., PAS suggests a product). If the customer is relieved from Consideration & Enactment, the customer still has to decide (e.g., PAS suggests a product, customer decides to purchase it, PAS orders the product). In the highest degree of autonomy, the customer is relieved from consideration, decision, and enactment (e.g., PAS identifies a product, decides to purchase it, and handles the order autonomously). *Customer benefits* determine the value proposition (e.g., efficiency gains and improved consumer experience). In contrast, *customer risk* determines the involved risk depending on the domain, and the individual task carried out by the service (Wuenderlich et al., 2013). The second layer *data* describes PAS functionality concerning the underlying data model and analysis. It comprises the dimensions of *data source*, *data analysis*, and *smartness*. *The data source* determines the number of heterogeneous sources used to provide highly customized services (Leyer et al., 2017). The manifestations of this dimension include personal (e.g., preferences, goals, activities) and contextual (e.g., weather, product availability) data (Hopf et al., 2017). Further, *data analysis* determines the data analysis capabilities at a specific point in time, and the service is used to process the data. PAS exhibit basic (i.e., descriptive) and extended (i.e., diagnostic, predictive, and prescriptive) data analysis capabilities (Allmendinger & Lombreglia, 2005; Porter & Heppelmann, 2015; Want et al., 2015). In contrast, *smartness* determines the handling of data over time: more precisely, learning and adapting (e.g., incorporating feedback) (Alter, 2019). The third layer describes the *interaction* between the PAS and customers, or among services. It comprises the dimensions of *trigger*, *representation*, and *integration*. *Triggers* determine the internal and external stimuli that initiate a service-related action based on the underlying data model (e.g., a proactive recommendation to the customer by the PAS). *Representation* determines how a service operates and interacts with customers. All PAS have a digital component, and some even have physical components. Finally, *integration* determines whether the service operates independently or with other entities in an ecosystem (Oberländer et al., 2018).

Influence of personality traits on CSAT

In this study, we are interested in how the manifestation of specific features of PAS affects CSAT. The Kano model is commonly used to describe CSAT based on implemented or possible but not yet implemented features of products or services (Kano et al., 1984; Matzler et al., 1996). The essential assumption in the so-called theory of attractive

quality is that the CSAT generated by a feature depends on the degree of performance or functionality in relation to customer expectations (Berger et al., 1993; Herzberg et al., 1959; Zhang et al., 2000; Kano et al., 1984) challenged the traditional understanding that the relationship between functionality and CSAT is linear, symmetric, and independent of the feature itself (Matzler et al., 1996; Nilsson-Witell & Fundin, 2005). The Kano model classifies product and service features into six qualities:

(1) *Attractive qualities* ("A") are appealing but not expected by customers. Their implementation has a highly positive effect, whereas their non-implementation does not affect CSAT.
(2) *One-dimensional qualities* ("O") are explicitly demanded by customers. Their implementation has a proportional positive effect, whereas their non-implementation has a proportional negative impact on CSAT.
(3) *Must-be qualities* ("M") are implicitly demanded by customers. Their implementation does not affect CSAT, whereas their non-implementation has a highly negative effect.
(4) *Indifferent qualities* ("I") are irrelevant to customers. Their implementation or non-implementation does not affect CSAT.
(5) *Reverse qualities* ("R") are rejected by customers. Their implementation has a highly negative effect, whereas their non-implementation positively affects CSAT.
(6) *Questionable results* ("Q") are those for which there are contradictions in customers' answers within a questionnaire.

However, this classification of service features based on CSAT is likely to vary depending on the personality traits of the customer. In the 1970s, there was considerable interest in satisfaction among scholars, and more than 5,000 research articles were published on the topic. It was reported among these articles that personality traits are related to satisfaction (Xiong, 2010). There are three separate streams in the literature:

In the first stream, the literature investigates the influence of personality traits on satisfaction. DeNeve and Cooper (1998), for example, found that conscientiousness, extraversion, and neuroticism are significantly related to satisfaction across many studies. Lounsbury et al. (2005) investigated whether personality traits are related to life satisfaction and concluded that extraversion, conscientiousness, neuroticism, and agreeableness were traits related to satisfaction. These studies used a multiple regression approach to obtain their results. In the second stream, the literature investigates the influence of personality traits on career satisfaction (encompassing all jobs across one's career) or job satisfaction (satisfaction with a specific

job) (Locke, 1976). In general, career or job satisfaction are essential drivers of CSAT (Homburg & Stock, 2004; Xiong, 2010). In many studies, researchers again investigated the relationship between personality traits and career or job satisfaction using multiple regression analysis and structural equation modeling (see Lounsbury et al., 2003; Matzler & Renzl, 2007). In the third stream, the literature investigates the relationship between personality traits and CSAT in different contexts (see Siddiqui, 2012; Castillo, 2017; Hsi-Jui Wu & Mursid, 2019; Ciunova-Shuleska & Palamidovska-Sterjadovska, 2019). Most related studies have aimed to establish a relationship between individual personality traits and purchasing behavior to predict the sales of expensive items such as cars (Siddiqui, 2012; Hsi-Jui Wu & Mursid, 2019), and Ciunova-Shuleska and Palamidovska-Sterjadovska (2019) focused their research on the relationship between personality traits and CSAT, particularly in the service field.

In terms of content, findings indicating that agreeableness, consciousness, extraversion, and openness tend to influence CSAT positively and neuroticism influences CSAT negatively were common across all research streams. All personality traits observed as independent variables in the above-mentioned research streams were FFM components. The FFM developed by Goldberg (1990) and Costa and McCrae (1992) is well established in psychology and is a standard method for measuring personality dimensions (Buettner, 2016; Matzler & Renzl, 2007; McCrae & Costa, 2004; Oliveira et al., 2013). This model is also known as "the Big Five" or "OCEAN" (Durupinar et al., 2011; Wiggins, 1996). The underlying idea is that five factors function as a comprehensive model describing higher-order differences between individuals according to many factors (Costa & McCrae, 1992). These five factors represent the basic dimensions of the human personality. Longitudinal and cross-observer studies have demonstrated the manifestation of the five factors in behavior patterns (Costa & McCrae, 1992; Schmitt et al., 2007). Further, the factors are found in various personality systems, in the natural language of trait description, and exhibit robustness in different age, sex, race, and language groups (Costa & McCrae, 1992; Schmitt et al., 2007). A personality trait often reflects the preferences, motivations, and values of a person and remains relatively stable over an entire lifetime (Buettner, 2016, 2017). By understanding their customers' personalities, companies are better able to provide suitable products and services (Buettner, 2017; Romero et al., 2009). The FFM divides personality into five traits:

(1) *Openness* is the tendency to be intellectually curious, creative, and multifaceted. A low level of openness is associated with being consistent and cautious. A high level of openness is associated with being inventive and curious.

(2) *Conscientiousness* is the tendency to be organized, purposeful, and self-controlled. A low level of conscientiousness is associated with being easy-going and careless. A high level of conscientiousness is associated with being efficient and organized.

(3) *Extraversion* is the tendency to be social, assertive, and talkative. A low level of extraversion is associated with being solitary and reserved. A high level of extraversion is associated with being outgoing and energetic.

(4) *Agreeableness* is the tendency to be sympathetic, helpful, and trusting. A low level of agreeableness is associated with being challenging and detached. A high level of agreeableness is associated with being friendly and compassionate.

(5) *Neuroticism* is the tendency to be emotionally stable, to control one's impulses, and to cope with stress. A low level of neuroticism is associated with being secure and confident. A high level of neuroticism is associated with being sensitive and nervous.

From a methodological perspective, it is common to the studies of all research streams mentioned above that the authors almost exclusively apply structural equation modeling to investigate the relationship between personality traits and satisfaction. Such structural equation modelling largely involved multiple regression analysis (Hair et al., 2016). The results of multiple regression analysis enable organizations to understand the influence of personality traits on CSAT. This approach determines whether the theories developed concerning the hypothesized relationship between the independent variables (i.e., FFM personality traits) and CSAT are valid. However, it is challenging to derive recommendations for design decisions based on these results. It is essential for service providers to not only know that personality traits influence CSAT, but also how their offerings should be tailored to achieve high CSAT. In its common application in research on satisfaction, structural equation modeling does not yield insights into the effects of individual service features on CSAT. Hence, a different approach is necessary to answer the research questions.

Both the Kano model and the FFM are seminal works in their disciplines. To date, researchers have yet to integrate both models in a combined approach. However, the combination of the two models would provide a unique perspective and novel insights. It would serve as a structured approach to analyze CSAT that is based on individual service features and customer personality traits. The results of this methodological approach could support the development of recommendations for designing services at the feature level. To the best of our knowledge, our study is the first to

investigate CSAT in the context of PAS using a design-oriented approach that explicitly considers the features of PAS.

Research method

Our research aimed to assess the effect of the features of PAS on CSAT by considering the potential moderating effect of customer personality traits. Therefore, we followed a three-step approach (Fig. 2). First, we developed the items for the survey, which were three questionnaires: the Kano questionnaire, the self-stated importance questionnaire, and the FFM questionnaire. Second, we implemented and conducted the survey. Third, we assessed responses to the questionnaires to answer our research question. All the steps and questionnaires are described in detail below.

Step 1 – Developing the items

In the first step, we developed items to measure the effect of the features of PAS on CSAT (Kano questionnaire), the importance of those features to customers (self-stated importance questionnaire), and the personality traits of customers (FFM questionnaire).

For the Kano questionnaire, we used the Kano model to analyze the impact of individual features of PAS on CSAT. While indirect approaches rely on observations, we used the Kano model as a direct survey approach. Participants answered the so-called functional ("If the feature is implemented, how would you feel?") and dysfunctional questions ("If the feature is not implemented, how would you feel?") (Kano et al., 1984; Matzler et al., 1996). For each feature, participants answered both questions using the following 5-point semi-quantitative scale: "I like it that way," "It must be that way," "I am neutral," "I can live with it that way," and "I dislike it that way." The Kano questionnaire items in our survey represented the features of PAS described in the taxonomy of Rau et al. (2020). Therefore, every taxonomy characteristic was converted into a Kano item by querying it in a functional and dysfunctional way. For instance, the PAS characteristic "Time" of the dimension "Customer Benefit"

was converted into the functional question, "If using the proactive service saves time and reduces one's effort, how do you feel?" and the dysfunctional question, "If using the proactive service does not save time and reduce one's effort, how do you feel?" To answer the functional and dysfunctional questions, participants chose one of the five previously mentioned possible answer options. To cover non-exclusive dimensions of the PAS taxonomy, we included additional items for the combination of characteristics (e.g., the "Data Source" dimension question "If the proactive services use both contextual and personal data, how do you feel?"). This approach resulted in 52 items (see Appendix Table 5).

In the self-stated importance questionnaire, we incorporated specific questionnaire items to allow for an enhanced interpretation of the responses by adding the importance of the features. Classifying the features of PAS as Kano model qualities depending on their effect on CSAT may already guide service design. However, when two features cannot be implemented simultaneously for technical or financial reasons, the classification cannot serve as the ultimate decision criterion (Matzler et al., 1996). For instance, a dilemma occurs when two features are classified as must-be qualities that are mutually exclusive due to technical or financial reasons (Chen & Chuang, 2008). Consequently, it is necessary to examine the perceived importance of the features of PAS from the customer's perspective (Berger et al., 1993). To further prioritize the features, Matzler et al. (1996) we recommend a self-stated importance questionnaire in addition to the Kano questionnaire. Customers rated the importance of each feature using a 5-point scale ranging from "not important" to "extremely important" (Berger et al., 1993). This approach produced 25 items. Service providers can obtain a precise understanding of feature importance with the results (Matzler et al., 1996).

For the FFM questionnaire, we combined the Kano model with the FFM to explore the moderating effect of personality traits on CSAT with the features of PAS. For operationalization, we determined the personality traits of all participants using a standard set of questionnaire items. Such sets of questionnaire items for the measurement of FFM personality traits exist as NEO inventories. Costa and McCrae (1992) developed the first NEO professional manual (NEO-PI) in
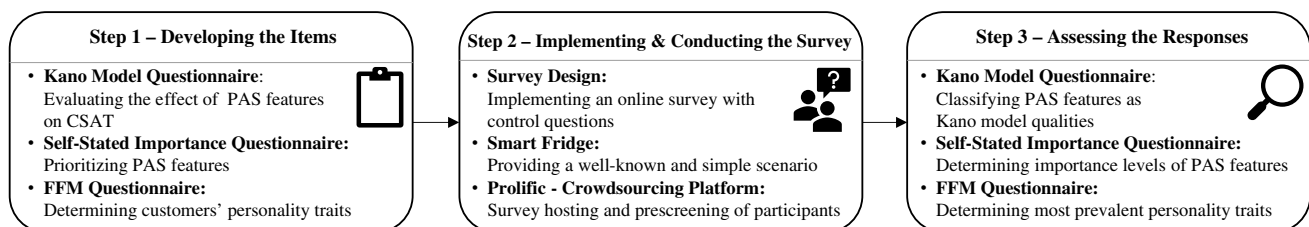

Fig. 2 Research method with three steps

1985. Over time, researchers have replaced items to increase clarity and understandability. Well-known and comprehensive questionnaires are the Revised NEO Personality Inventory (NEO-PI-R) and the NEO Personality Inventory Third Edition (NEO-PI-3), each containing 240 items. A shorter version is the NEO Five-Factor Inventory-3 (NEO-FFI-3), with 60 items, providing a quick, reliable, and accurate measurement of the five personality traits. This shorter version is beneficial when the participants' time is limited. All inventories are available in two versions: Form S for self-reports and Form R for observer ratings. Researchers commonly use Form S and formulate items in the first person. Form R is used for peer or expert ratings and is written in the third person. Each item belongs to one of the personality traits and is measured on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." Each item is scored from 0 to 4. However, there are items marked with an "R" that are measured in the Likert scale's reverse order. Within the FFM questionnaire, we used the NEO-FFI-3 inventory in Form S to measure personality traits. Therefore, we measured each factor of the FFM using the 12 standard items.

Step 2 – Implementing and conducting the survey

Building on the Kano model, the self-stated importance method, and the FFM questionnaires described above, we conducted an online survey to assess the features of PAS. We decided to use a smart fridge as a specific, well-known, and simple scenario for the survey to provide participants with a realistic example and to ensure the understandability of the PAS concept (Liu et al., 2018). A smart fridge is an object of daily life that evolves into a PAS by analyzing customer preferences and anticipating customers' needs. For instance, a smart fridge analyzes grocery consumption and customer preferences to generate personalized shopping lists or even re-order groceries that are about to run out. With the help of an explanation video[1] at the beginning of the survey, we ensured that every participant had the same knowledge of PAS in general and understood the smart fridge.

To ensure high-quality results, the survey included control questions (e.g., "If you answer this survey cautiously, check the second box from the left," "Have you watched the explanation video?" and "Have you responded accurately and honestly?") (Hair et al., 2016). We further conducted a pre-test with 15 participants that we excluded from the later main survey and adjusted the survey according to their feedback (Summers, 2001). For instance, we revised the survey to be easily accessible on mobile devices, which increased the response rates. To improve understandability, we revised some items so that the survey was comprehensible from a participant's point of view, as recommended by Berger et al. (1993). We conducted both the pre-test and the online survey on the crowdsourcing platform Prolific (https://prolific.ac) within a period of two weeks. Prolific prescreens survey participants to exclude bots in the population and maintain reliable data quality. For our survey, we only invited participants who currently reside in the United States or the United Kingdom to avoid language barriers. The second screening filter considers technology and online behavior to include participants with experience that matches the underlying smart fridge scenario. Therefore, we invited participants who owned smart kitchen appliances (e.g., fridge, oven) and shopped for groceries with the help of an Internet-connected device (e.g., Amazon Dash Button, Hiku, GeniCan). Accordingly, we used a non-probability sampling procedure. More precisely, we used a convenience sample because the sub-population, determined by the set filters, could easily be compiled via Prolific. With a different sampling procedure, the population is not really ascertainable, because the survey requires a technology-savvy target group that is very active on the Internet. The bias created by a convenience sample is therefore manageable due to the use of Prolific.

The main survey yielded 259 valid responses, with no missing values. There was no evidence of any systematic bias in the survey that could have caused premature abandonment. Since all the questions were mandatory, we did not test for nonresponse bias (Armstrong & Overton, 1977). The participants were aged between 18 and over 60 years (average age 23.5 years). The survey was completed by both women (45%) and men (55%) from the United Kingdom and the United States. Most of the participants were well-educated, as the percentage of participants holding a university degree was 60%. Because of the participants' experience with smart kitchen appliances, we use the term "customer" instead of "participant" in the next sections describing the analysis and interpretation of the results.

Step 3 – Assessing the responses

In the third step, we evaluated the survey responses. First, we analyzed each questionnaire separately. Second, we combined the results of the three questionnaires for an integrated analysis.

For the Kano questionnaire, each possible combination of the answers to the functional and dysfunctional questions determines the classification of the features of PAS according to the Kano model, as displayed in Table 1 (Kano et al., 1984; Matzler et al., 1996).

The easiest and most intuitive way to determine the Kano model quality of a feature among all participants is to select the classification result that appears most often, that is, the mode (Berger et al., 1993). However, this classification is often ambiguous and requires further examination to prevent

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[1] https://youtu.be/92ktPyMX3KM.

Table 1 Kano evaluation table (Berger et al., 1993)

One Customer's Answers for a Feature of PAS		Dysfunctional Answers				
		I like it that way	It must be that way	I am neutral	I can live with it that way	I dislike it that way
Functional Answers	I like it that way	Q	A	A	A	O
	It must be that way	R	I	I	I	M
	I am neutral	R	I	I	I	M
	I can live with it that way	R	I	I	I	M
	I dislike it that way	R	R	R	R	Q

Qualities: A = Attractive, O = One-dimensional, M = Must-be, I = Indifferent, R = Reverse, Q = Questionable

misleading interpretations if participants' answers lead to similar frequencies of one feature's qualities (Schaule, 2014). The mode only represents the preferred quality if a significance test supports this hypothesis. We tested this significance using the criterion category strength, that is, the relative difference between the most and second-most frequent quality of one feature (Lee & Newcomb, 1996). The Fong test is a more sophisticated method of testing for such significance which has been used in several studies (Gimpel, Kleindienst, Nüske, et al., 2018; Zhao & Dholakia, 2009). Fong (1996) assumes the mode as the correct quality if the category strength is higher than a threshold, which depends on the observed frequencies and sample size. As a rule of thumb, a category strength higher than 6% indicates a significant categorization with a probability of 90% (Lee & Newcomb, 1996). Hence, we used the Fong test with a 6% threshold and category strength as the criterion.

If the classification based on the mode is not significant, Berger et al. (1993) propose to use the (A, O, M) <> (I, R, Q) rule. This rule is applicable if one of the most and second most frequently appearing classifications belongs to the group of qualities that influence CSAT (A, O, and M), and the remaining one belongs to the group of qualities that do not influence CSAT (I, Q, and R). Applying this rule determines a single quality for the feature that is the most frequently appearing classification within the respective group (A, O, M) or (I, Q, R). If the (A, O, M) <> (I, R, Q) rule is not applicable, Lee and Newcomb (1996) recommend a mixed group.

In the present study, we assigned qualities to the features based on the mode if the category strength was significant according to the Fong test with a threshold of 6%. If the category strength was not significant, we executed the (A, O, M) <> (I, R, Q) rule, if applicable. Otherwise, we assigned the feature to a mixed group by listing all qualities that did not significantly differ according to the Fong test compared with the most frequently selected one.

For the self-stated importance questionnaire, the degree of importance was calculated for each feature using the average of the item responses. Therefore, we divided the degree of importance into two categories: high and low. A feature was assigned to high importance if the degree of importance was greater than the mean of importance for all features of PAS and low if it was below the mean (Yang, 2005) refined the Kano model by differentiating its qualities by importance, as outlined in Table 2. In the present study, we determined the degree of importance of all features. Based on the refined Kano model, we compared the results with those of the Kano model, allowing further interpretation and prioritization of the features in the PAS design process.

Regarding the FFM questionnaire, one participant's responses were calculated separately for each of the five personality traits by summarizing the values of the respective item responses. The total sum is called the raw score and has little meaning (McCrae & Costa, 2004). Raw scores were converted into T-scores, a pre-defined scale for interpretation and analysis. T-scores indicate how many standard deviation units a participant's raw score is above or below the mean compared to a population-representative norm sample from the NEO-FFI manual (Costa & McCrae, 1992). T-scores of 56 or higher were considered high, T-scores between 45 and 55 were considered average, and T-scores of 44 or lower were considered low (McCrae & Costa, 2004).

Table 2 Quality attributes in the refined Kano model (Yang, 2005)

	High importance	Low importance
Attractive	Highly attractive	Less attractive
One-dimensional	High value-added	Low value-added
Must-be	Critical	Necessary
Indifferent	Potential	Care-free

In the present study, we calculated the T-scores for every participant and for each personality trait (McCrae & Costa, 2004). To combine the Kano model with the FFM, we divided the sample into five subsamples using a segmentation method (Cooil et al., 2008). To this end, we assigned each participant to one subsample based on their highest T-score. Consequently, all participants were grouped according to their most prevalent personality trait from the FFM, following the approaches of Anderson et al. (2008), Cooil et al. (2008), and Siddiqui (2012). We then applied the Kano model to every subsample. This segmentation helped us analyze whether personality traits influence customer satisfaction by implementing individual features of PAS.

Results

This section presents the results of the analysis of the data from the online survey, which included the Kano, self-stated importance, and FFM questionnaires. First, we outline the customer assessments of the features of PAS, as indicated by the results of the Kano and self-stated importance questionnaires. Next, we further refine this analysis with a differentiated view of the assessment based on customers' most prevalent personality traits, as determined by the FFM questionnaire.

Customer satisfaction with the features of PAS

Our first analysis focused on customer assessments of the features of PAS, as determined with the Kano and self-stated importance questionnaires. The results of this analysis can help service providers prioritize features of PAS based on their effect on CSAT. Table 3 presents an overview of the results sorted by descending self-stated importance. For each feature, the table reports the relative frequency of the Kano model qualities classified by the customers and the corresponding category strength. Incorporating self-stated importance, the (A, O, M) < > (I, R, Q) rule, and mixed groups, the table presents the final Kano classification of all features of PAS.

We first addressed three key general findings and then analyzed the results in detail based on the Kano model qualities. The three key general findings were as follows: First, the results showed that customers highly value the benefits of PAS (F5, F4, F8, F7, F6). Customers classify the benefits as attractive or indifferent qualities, but with high potential and high importance. Second, customers highly value proactivity as long as they themselves are involved in the decision process (F1, F2). However,

customers tended to refuse the most advanced archetype autopilot, when PAS decide on behalf of the customer (F3). Third, customers have paradoxical views about the associated risks of PAS, according to the results of the self-stated importance questionnaire. On the one hand, customers appreciate the reversibility options of decisions and prefer that PAS not be involved in high-impact decisions (F11, F9). On the other hand, customers seem to be careless in providing their personal data and consider it less important to reduce the risk involved (F10, F12, F14).

In addition to the key findings, our results provide insights into detailed customer preferences regarding PAS in terms of Kano model qualities. Customers classified seven features of PAS as attractive qualities (F1, F4, F8, F7, F17, F15, F21). Two additional features were most frequently classified as attractive qualities in the mixed groups (F5, F2). The implementation of features classified as attractive qualities delights customers. However, customers do not expect their implementation. Hence, we recommend implementing features with attractive qualities to positively surprise customers and to differentiate the services provided from other competitive services. Attractive qualities can be found predominantly among the benefit dimensions of the taxonomy of PAS (F4, F7, F8). Moreover, customers are delighted by proactive information on available decision options (F1), self-learning ability (F17), analysis of their data to improve recommendations (F15), and the use of a social trigger (F21). However, the last two features are less important to customers, although customers consider them attractive. A possible reason for this is that these features are part of the technical design of PAS, and customers do not see the direct value of the features (Lee & Lee, 2020). Thus, service providers should focus on features classified as attractive and highly important to customers.

Only features in the mixed groups were classified as one-dimensional and must-be qualities. One-dimensional qualities have a positive effect on CSAT if implemented, and a negative effect if not implemented. Must-be qualities are expected by customers. The non-implementation of features with a must-be quality leads to dissatisfaction, whereas their implementation has no positive effect on CSAT. We classified reversibility (F11) as a mix of one-dimensional and must-be qualities. This feature is highly important to customers. Thus, service providers must include this feature in their PAS design to avoid customer dissatisfaction. The integration of the reversibility feature creates a sense of security for customers, as they can quickly reverse decisions made by PAS. Customers did not classify other features of PAS as

Table 3 Empirical results of the Kano model analysis of the features of PAS

	#	Feature	Self-stated Importance Rank	Self-stated Importance Mean	A [%]	O [%]	M [%]	I [%]	Q [%]	R [%]	Category Strength [%]	Classification Kano	Refined Kano
High Importance	F5	Money Benefit	1	4.80	33.2	32.05	10.42	21.24	0.39	2.7	1.16 [a]	Mixed (A, O)	Highly Attractive, High Value-Added
	F1	Consideration	2	4.71	27.8	22.01	15.06	31.66	0.77	2.7	3.86 [b]	A	Highly Attractive
	F4	Time Benefit	3	4.69	43.24	20.85	9.65	24.32	-	1.93	18.92*	A	Highly Attractive
	F8	More than one Benefit	4	4.62	37.84	19.69	16.99	24.71	0.39	0.39	13.13*	A	Highly Attractive
	F7	Better Quality	5	4.61	29.34	26.64	15.83	27.8	-	0.39	1.54 [b]	A	Highly Attractive
	F2	Consideration & Enactment	6	4.61	26.64	30.5	18.92	20.08	0.39	3.47	3.86 [a]	Mixed (O, A)	High Value-Added, Highly Attractive
	F11	Reversibility	7	4.52	7.72	40.15	39.38	12.36	-	0.39	0.77 [a]	Mixed (O, M)	Highly Value-Added, Critical
	F6	More Flexibility	8	4.41	30.89	16.99	12.74	37.84	0.39	1.16	6.95*	I	Potential
	F17	Self-Learning Ability	9	4.19	26.25	23.17	18.53	25.87	0.77	5.41	8.88*	A	Highly Attractive
	F23	Digital Representation	10	4.12	28.57	23.17	8.88	37.45	-	1.93	0.39 [b]	I	Potential
	F25	Integration into Ecosystem	11	4.01	27.41	18.53	8.49	38.22	0.39	6.95	10.81*	I	Potential
Low Importance	F24	Physical & Digital Representation	12	3.81	27.41	20.08	4.63	45.95	-	1.93	18.53*	I	Care-free
	F20	Time Trigger	13	3.8	22.39	9.65	7.34	54.44	0.77	5.41	32.05*	I	Care-free
	F15	Basic Data Analysis	14	3.77	32.43	15.44	10.42	37.07	0.39	4.25	4.63 [b]	A	Less Attractive
	F16	Extended Data Analysis	15	3.73	28.96	13.9	6.95	43.24	-	6.95	14.29*	I	Care-free
	F10	Limited Customer Risk	16	3.60	29.34	13.13	8.88	38.22	0.39	10.04	8.88*	I	Care-free
	F22	More than one Trigger	17	3.59	25.48	12.74	8.49	49.03	1.54	2.70	23.55*	I	Care-free
	F12	Personal Data	18	3.57	22.39	16.22	5.41	31.27	0.77	23.94	7.34*	I	Care-free
	F18	Event Trigger	19	3.47	23.17	11.58	10.81	48.26	-	6.18	25.10*	I	Care-free
	F19	Location Trigger	20	3.28	24.32	5.02	2.32	57.92	0.77	9.65	33.59*	I	Care-free
	F13	Contextual Data	21	3.27	25.87	10.04	3.86	46.33	0.77	13.13	20.46*	I	Care-free
	F9	Substantial Customer Risk	22	3.17	9.65	0.00	2.32	41.70	0.39	45.95	4.25 [a]	Mixed (R, I)	Reverse, Care-free
	F21	Social Trigger	23	3.16	29.73	13.51	8.11	35.14	0.77	12.74	5.41 [b]	A	Less Attractive
	F14	Personal & Contextual Data	24	2.42	18.92	10.81	3.09	44.02	0.39	22.78	21.24*	I	Care-free
	F3	Consideration, Decision & Enactment	25	2.04	13.13	6.95	3.09	30.89	-	45.95	15.06*	R	Reverse

*Classification significant at the 6% level

[a] (O + A + M) < > (I + R + Q) rule non-applicable

[b] (O + A + M) < > (I + R + Q) rule applicable

A = Attractive Quality; O = One-dimensional Quality; M = Must-be Quality; I = Indifferent Quality;

R = Reverse Quality; Q = Questionable Result

one-dimensional or must-be qualities. This finding may be due to customers' low level of experience with PAS, as these services are a comparably new phenomenon.

Customers classified most features of PAS as indifferent qualities. As indifferent qualities do not influence CSAT, service providers cannot draw any distinctive interpretations regarding the current design of PAS. Nevertheless, Sauerwein (1999) suggested that the difference between attractive and indifferent qualities is often very small. Our results confirm this assumption; out of the 13 features for which their most frequent classification was indifferent, eleven had the second-most frequent classification of attractive. The self-stated importance analysis provides more insight into whether these features should be considered in the design of PAS. More flexibility (F6), digital representation (F23), and integration into ecosystem (F25) were assessed with a high degree of importance, and thus were given the refined Kano classification of having potential qualities. These features potentially attract customers and gradually become attractive qualities. Accordingly, service providers can consider these features as "strategic weapons" to increase CSAT in the future. For example, for the feature integration into the ecosystem (F25), service providers can think of possible partnerships right from the beginning and design the service with the possibility of integrating various interfaces. Later, linking to a partner or interface can be implemented without high set-up costs. Further, PAS can provide more significant benefits when they interact with other services (e.g., every family member is connected to the smart fridge so that food reordering is aligned with the consumption of all family members). In addition, the indifferent qualities pertaining to the technical design of PAS are of low importance to customers. This includes, for instance, diverse triggers (F20, F22, F18, F19), its digital and physical representation (F24), and the use and analysis of data (F16, F13). Customers may assume smooth functioning of these technical features of PAS as a standard in the digital age (Lee & Lee, 2020).

Customers classified two features as reverse qualities, of which one occurred in a mixed group. The implementation of reverse qualities leads to customer dissatisfaction. Our study results show that customers avoid (or are indifferent to) using PAS for high-impact decisions (F9). Further, customers refrain from being relieved from consideration, decisions, and enactment (F3). The latter feature is also the least important feature for customers. The classification results for both features explain customer risk aversion. Customers are not yet willing to transfer decision power, particularly for high-risk decisions, to the PAS. However, we recommend that service providers further analyze these features when customers have more experience with PAS, are accustomed to more advanced PAS types, and are open to algorithmic decision-making.

Our study did not yield any questionable results for the responses to the Kano questionnaire. The absence of questionable results confirms the comprehensibility of our survey, with no ambivalence or errors in the results. In sum, the results show that customers classify most features of PAS as indifferent qualities and a handful of features as attractive qualities, but so far, there is little demand for any specific features to be standardized.

Customers satisfaction differentiated by personality traits

To analyze how personality traits influence customer classification with the features of PAS, and thus with CSAT, we conceptually combined the Kano model and customers' self-stated importance of the features with the FFM. Therefore, we assigned each customer to one segment (i.e., subsample) based on their highest T-score, so that in the end, all customers were grouped by their most prevalent personality trait according to the FFM, following the approaches of Anderson et al. (2008), Cooil et al. (2008), and Siddiqui (2012). For instance, a customer with openness as the most prevalent personality trait was grouped into the 'Openness' segment. We then applied the Kano model to each segment. Table 4 shows the final classifications of all features of PAS in each segment (i.e., the Kano model classifications based on the most prevalent personality trait of the customers). Similar to the previous analysis, we sorted all features of PAS by descending self-stated importance.

To describe the results of this advanced analysis, we again highlight three key findings valid across all segments and then present the results of our detailed analysis, which was based on the most prevalent personality traits.

First, there were no contradictions between these results and those of the non-segmented Kano model analysis. Some features, such as time benefit (F4), triggers (F20, F18, F19), and features pertaining to data use and analysis (F13, F14) were classified identically across all segments. Second, the segmented analysis allowed for a more detailed interpretation of that features of PAS that were classified as indifferent. We were able make clearer statements for up to 50% of the features previously classified as indifferent qualities. For instance, the features digital representation (F23) and integration into ecosystem (F25) were previously classified as indifferent and are now classified as attractive or one-dimensional qualities depending on the segment. Third, we obtained a deeper understanding of the key findings of the classical Kano analysis, which had indicated that customers' highly value the benefits and the proactive nature of PAS, and engage in paradoxical behavior in terms of risk and provision of data. Customers, for example, not only desire high

Table 4 Empirical results of the Kano model analysis segmented by the most prevalent personality traits

	#	Feature	Classification - Segmented Kano				
			Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
High Importance	F5	Money Benefit	A	A	O	O	O
	F1	Consideration	A	A	O	A	A
	F4	Time Benefit	A	A	A	A	A
	F8	More than one Benefit	A	A	Mixed (O, A, I)	A	A
	F7	Better Quality	A	A	O	O	M
	F2	Consideration & Enactment	Mixed (O, A)	Mixed (A, O, M, I)	O	O	A
	F11	Reversibility	Mixed (O, M)	M	O	O	M
	F6	More Flexibility	I	A	I	I	I
	F17	Self-learning Ability	M	Mixed (A, O, M, I)	Mixed (A, O, I)	A	A
	F23	Digital Representation	A	A	I	O	I
	F25	Integration into Ecosystem	I	A	A	I	I
Low Importance	F24	Physical & Digital Representation	I	A	I	I	I
	F20	Time Trigger	I	I	I	I	I
	F15	Basic Data Analysis	A	Mixed (A, O, I)	I	A	I
	F16	Extended Data Analysis	A	I	I	I	I
	F10	Limited Customer Risk	I	A	I	A	I
	F22	More than one Trigger	I	A	I	I	I
	F12	Personal Data	I	A	I	I	R
	F18	Event Trigger	I	I	I	I	I
	F19	Location Trigger	I	I	I	I	I
	F13	Contextual Data	I	I	I	I	I
	F9	Substantial Customer Risk	R	R	R	I	R
	F21	Social Trigger	I	A	A	A	A
	F14	Personal & Contextual Data	I	I	I	I	I
	F3	Consideration, Decision & Enactment	Mixed (R, I)	R	R	R	R

A = Attractive Quality; O = One-dimensional Quality; M = Must-be Quality; I = Indifferent Quality;

R = Reverse Quality; Q = Questionable Result

value but also demand benefits (F5, F8, F7), customer-controlled proactivity (F1, F2), and/or self-learning ability (F17), depending on the segment manifested in the classification as must-be and one-dimensional qualities. Further, it is clear that customers accept a reasonable level of risk. In the segmented Kano analysis: customers classified substantial customer risk (F9) as a reverse quality in four out of five segments and limited customer risk (F10) as an attractive quality in two out of five segments. In addition to these three key findings, we present

segmented results depending on the most prevalent personality traits. Therefore, we highlight the overall picture and peculiarities in the sense of features classified differently across segments.

Customers with a high level of openness are curious and open-minded about PAS. In this segment, we classified many features as attractive qualities, but customers require that PAS have a self-learning ability (F17) to provide more personalized services. Moreover,

customers classified the archetypal feature autopilot (F3) as a mix of reverse and indifferent qualities. Thus, customers with a high level of openness could serve as pilot customers for an advanced service with high autonomy, as this segment does not fully reject this service configuration.

Customers with a high level of conscientiousness are also enthusiastic about PAS. This enthusiasm is evident in their classification of many of the features as attractive qualities and not as indifferent. However, conscientious customers have an organized nature and are self-controlled. This aspect is reflected in the classification of features that involve delegating decisions. For them, it is challenging to classify the features consideration and enactment (F2), self-learning ability (F17), and basic data analysis (F15), as these features hand over control to the service. These organized and self-controlled customers are highly likely to require reversibility options (F11) and decline features that give the service more autonomy and involve high risk (F3, F9).

Customers with a high level of extraversion and agreeableness have a clear vision of what they desire in PAS. They already require that certain features with high importance to customers are displayed in diverse one-dimensional quality classifications. They appreciate and demand the ability to delegate decisions when reversibility options are included in the service (F2, F11). However, they still want to have control, and are unlikely to use autonomous options of PAS. Extroverted customers with an outgoing nature prefer the integration to an ecosystem (F25) but are indifferent toward many features, such as personal data (F12) or limited customer risk (F10). In addition, agreeable customers with trust in PAS have a paradoxical attitude toward risk. On the one hand, they are aware of the limited risk of delegating decisions. On the other hand, they are indifferent to substantial customer risk (F9), a feature that is otherwise classified as reverse quality. The results indicate that these customers are eager to maintain control, potentially due to their limited experience with highly autonomous PAS.

Customers with a high level of neuroticism, characterized by a sensitive nature, demand high security standards and benefits. They are also very skeptical about providing personal data and even avoid PAS. However, it is difficult for service providers to offer personalized services with matching benefits without using personal data. When designing PAS for customers with a high level of neuroticism, tact and sensitivity are required.

Discussion

This study yielded two major insights: (1) customers currently do not value features that give PAS autonomy over decisions and (2) they engage in paradoxical behavior when assessing the use of personal data. Both insights have considerable implications for the future design of PAS and their acceptance by customers.

First, customers are very skeptical about PAS configurations that allow the service to have a high level of autonomy. At present, such features have a highly negative effect on CSAT. Customers tend to be reluctant to give up control and, consequently, often hesitate to delegate decision-making, even when it could be beneficial from an objective point of view (Steffel et al., 2016). This phenomenon has already been noted in other research, particularly in cases where the customer has little experience using an autonomous system. For instance, Baier et al. (2018) investigated customer satisfaction in different conversational commerce use cases. Four use cases were found to be "customer passive"; that is, customers received information, offers, or recommendations from an autonomous system. Customers classified these use cases as "reverse," that is, as not preferred. These findings can be attributed to the novelty of the autonomous system and the lack of experience among the customers (Baier et al., 2018; Leyer & Schneider, 2019). Customers who are more familiar with the technology evaluated the use cases differently and with much greater enthusiasm (Baier et al., 2018; Leyer & Schneider, 2019) investigated the willingness to transfer strategic decision-making to AI-based systems among managers. Their findings revealed that managers are less likely to delegate a decision to AI. However, customers were less emotional about the outcomes when they delegated responsibility to an AI-enabled system than when they delegated responsibility to another person.

In sum, the research confirms customers' current rejection of the autonomous decision-making of PAS. However, there is an increasing demand for autonomous systems in the digital age (Shifflet-Chila et al., 2016). The autonomy of systems is likely to become a key value

driver for organizational efficiency and effectiveness, particularly in data-intensive environments (Leyer & Schneider, 2019). This autonomy can be valued as a benefit, a component of well-being, or as a personal value (Darwall, 2006). As the degree of autonomy impacts service usage, service providers need to carefully consider whether PAS adds substantial value, especially when customer experience is still low (Leyer & Schneider, 2019). Thus, we recommend providing a sufficient explanation when introducing a PAS with high levels of autonomy. A precise explanation of what the service is doing helps build customer trust and even the intention to act (Herlocker et al., 2000). This approach is known as explainable AI. Explainable AI represents the extension of AI by making suggestions of an AI more traceable for customers following strategies and methods from human-computer interaction research and the social sciences (Miller, 2019). Further, service providers should first offer PAS with high levels of autonomy in non-critical areas (e.g., tasks done regularly, with little monetary risk, and almost zero negative impact on one's life) and integrate the possibility of reversing an autonomously made decision as a fallback option. In this way, customers gain familiarity, acquire experience in transferring control, and therefore learn to appreciate the advantages of PAS. Accumulation of experience enables a stepwise transition to PAS with higher levels of autonomy.

Second, PAS require large volumes of personal data to create personalized offerings. Personal data about customers and data analysis capabilities are a prerequisite for the functioning of PAS and the fulfillment of their unique value propositions. Our results reveal that customers are generally skeptical about providing personal data. However, if they receive an extrinsic benefit (e.g., monetary savings or time savings), an intrinsic benefit (e.g., pleasure or novelty), or face social pressure, they do not behave rationally in terms of the risk-benefit trade-off (Cichy et al., 2021; Gimpel, Kleindienst, & Waldmann, 2018; Hui et al., 2006). This phenomenon is known as the privacy paradox. This may be explained by trust in the service provider, a lack of risk awareness, a lack of knowledge about privacy-protective behaviors, or the social advantages of self-disclosure (Ebbers et al., 2021; Hargittai & Marwick, 2016; Kokolakis, 2017). The same data which brings significant advantages for service providers also increases customer privacy concerns (Hauff et al., 2015; Zhan & Rajamani, 2008). This circumstance poses a dilemma for service providers.

Therefore, we suggest the following privacy-by-design approach when offering PAS. The idea of privacy-by-design is to identify and investigate potential privacy issues and to incorporate privacy protection into the overall design early, rather than finding tedious and time-consuming solutions later (Schaar, 2010). Further, trust is a fundamental prerequisite for establishing and growing online services (Hoffmann et al., 2016). Therefore, service providers should provide complete transparency in using personal data and guarantee data protection so that customers can build trust in data processing. Additionally, service providers can identify privacy-sensitive customers as a specific customer segment and serve this segment with a standardized PAS (i.e., using little or no personal customer data). Service providers can use the privacy paradox metric proposed by Gimpel, Kleindienst, and Waldmann (2018) to identify whether a customer behaves paradoxically. This metric identifies careless customer decisions regarding data disclosure and manages the risks related to such decisions. Service providers can provide warnings at the point of possible data disclosure and suggest alternative services that better fit the customer's privacy intentions.

Abstracting from the two above-mentioned insights, a detailed analysis of all classical and segmented Kano model results leads to additional theoretical and managerial implications. With regard to the theoretical implications, our research extends the body of knowledge on PAS by providing an empirical understanding of customers' assessment of the features of PAS and having a differentiated view of customer satisfaction that is based on personality traits. Further, our research demonstrates the applicability of the taxonomy developed by Rau et al. (2020) in gaining a deeper understanding of the PAS phenomenon. Ultimately, our research builds a foundation for more enhanced theories in the PAS context (e.g., theory of design and action) (Gregor, 2006).

Using theoretical arguments and empirical evidence on the explanatory power of personality traits on CSAT, we also provide a methodological augmentation of the Kano model. Use of the Kano model among customers with low experience often leads to the classification of features as indifferent qualities (Baier et al., 2018). However, we can make more refined interpretations of the potential of indifferent classified features by combining the Kano model with the FFM and incorporating customers' self-stated importance of features. Thus, our approach of combining the aforementioned

methods can be seen as a blueprint for further conceptual developments of the Kano model.

Beyond its theoretical implications, this study also has managerial implications. First, our research provides evidence supporting the idea that the features of PAS contribute differently to CSAT, allowing for a feature-based design. In this way, our results enable service providers to develop competitive service designs by incorporating customer perspectives on aspects beyond the technical ones. Further, the prioritization of features based on the expected CSAT allows service providers to start with features that provide direct value to customers that can be more easily monetized. This ability is essential to increasing customer acceptance of PAS, as the price-value trade-off is an established antecedent in acceptance research (Venkatesh et al., 2012). Thus, service designers can use our approach to assess the theoretical configurations of PAS ex ante (e.g., before a practical implementation), thus saving resources. Second, our research demonstrates that the features of PAS contribute differently to CSAT depending on customers' most prevalent personality traits. Therefore, service providers should consider the personality traits of their customer base in the design of PAS. However, further research is required to determine whether service providers should configure PAS for specific customer archetypes. Such a personality trait-orientated perspective may result in more satisfied customers and a higher business value. Third, our research provides insights into the features of PAS that require additional effort from service providers for implementation. For example, service providers should mitigate the risk of refusal by customers by establishing trust-building measures for autonomous systems or introducing additional measures (e.g., marketing measures) to overcome reservations.

Conclusion, limitations, and further research

This study contributed to the knowledge of the emerging concept of proactivity and autonomy in the service field, known as PAS, by providing insights for PAS design associated with high CSAT. To this end, we combined three methods: the Kano model, self-stated importance, and FFM. The application of the Kano model and self-stated importance allows for the prioritization of the features of PAS depending on their impact on CSAT. In combination with the FFM, our study highlights differences in the prioritization of the features of PAS

depending on the customers' most prevalent personality trait and thus making clearer statements of PAS preferences for up to 50% of the features otherwise classified as indifferent in terms of the Kano model.

Overall, we found that customers are still skeptical of PAS with high levels of autonomy, and that customers behave paradoxically in risk-benefit trade-offs created by PAS. However, the results provide service providers with insights into the configuration of PAS associated with high CSAT. Such specific guidance on a feature level is helpful to service designers, especially when introducing new or reconfiguring existing PAS. Thus, our work may increase the adoption rates of existing and future PAS.

This study had several limitations. First, our results were based on data collected from the United Kingdom and the United States. Hence, our results may not be generalizable to other countries due to various economic and cultural reasons, and in other PAS use cases. Future research should use data from different countries and different PAS use cases to validate and extend the generalizability of our findings. Second, we used a segmentation method by dividing the sample based on the customers' most prevalent personality trait as determined with the FFM. This approach efficiently allowed us to integrate the personality perspective in the Kano model, but it only provides an approximation of customers' real personalities. Future research should employ cluster analysis to identify customer archetypes in a more sophisticated manner and to assess the prioritization of the features of PAS more precisely. Accordingly, service providers can design PAS for a specific customer type, potentially leading to even higher CSAT. Third, PAS is an emerging concept, and so far, customers have little experience with this type of service. This circumstance results in customers predominantly assessing the features of PAS as indifferent. According to Kano's lifecycle theory, the assessment of features changes over time with changing perceptions by customers (Kano, 2001). Qualities viewed as indifferent may become attractive, one-dimensional, or must-be qualities. Thus, our results are not stable in the long run. Future research should validate and refine the assessment of the features of PAS from time to time, to provide a contemporary basis for determining those design options of PAS that improve CSAT.

Appendix 1

Table 5 Items of the Kano questionnaire

Dimension	Characteristic		Item
Customer Relief	F1	Consideration	Provision of information, recommendations, or options by the service, the decisions to use the information is up to the customer (e.g., smart fridge proposes a shopping list).
			No provision of information, recommendation, or options.
	F2	Consideration & Enactment	The customer decides, and the service executes the decision (e.g., smart fridge orders proposed shopping list with your consent).
			No execution of decisions.
	F3	Consideration, Decision & Enactment	Autonomous decision and execution on behalf of the customer (e.g., smart fridge orders the identified shopping list autonomously).
			No autonomous decision and execution on behalf of the customer.
Customer Benefit	F4	Time Benefit	Time benefits (e.g., time savings and reduced effort).
			No time benefits.
	F5	Money Benefit	Money benefits (e.g., money savings).
			No money benefits.
	F6	More Flexibility	More flexibility (e.g., provision of suitable options or simplification of orders).
			No more flexibility.
	F7	Better Quality	Better quality (e.g., improvement of customer experiences, such as an increase of positive emotions).
			No better quality.
	F8	More than one Benefit	More than one of the benefits mentioned above.
			Not more than one of the benefits mentioned above.
Customer Risk	F9	Substantial	Involvement of high-impact decisions (e.g., a smart fridge is allowed to order expensive and short-lasting products).
			No involvement of high-impact decisions.
	F10	Limited	Involvement of low-impact decisions (e.g., a smart fridge is allowed to order cheap and long-lasting products).
			No involvement of low-impact decisions.
	F11	Reversibility	Reversibility of decision (e.g., you can easily cancel the orders).
			No reversibility of decisions.
Data Source	F12	Personal Data	Use of your personal data such as preferences, goals, activities, and everyday routine (e.g., customers' personal diet).
			No use of your personal data.
	F13	Contextual Data	Use of your contextual data (e.g., customers' environment such as weather, broader market change, or news).
			No use of your contextual data.
	F14	Personal & Contextual Data	Use of both contextual and personal data.
			No use of combined data.
Data Analysis	F15	Basic Data Analysis	Descriptive analytics (e.g., a smart fridge provides proactive services based on rules and simple calculations).
			No use of descriptive analytics.
	F16	Extended Data Analysis	Diagnostic, predictive, and prescriptive analytics (e.g., smart fridge provides proactive services based on more complex methods such as prediction models).
			No use of diagnostic, predictive, and prescriptive analytics.
Smartness	F17	Self-learning Ability	Ability to adapt to changing needs and preferences and incorporate feedback (e.g., a smart fridge can understand changes in your preferences).
			No ability to adapt to changing needs and preferences.

Table 5 (continued)

Dimension	Characteristic		Item
Trigger	F18	Event Trigger	Triggered by a detectable change in your circumstances (e.g., you took groceries out of the fridge).
			Not triggered by detectable change.
	F19	Location Trigger	Triggered by local occasions (e.g., weather or geographical location).
			Not triggered by local occasions.
	F20	Time Trigger	Triggered by temporal deadlines (e.g., time of the day, month, or season).
			Not triggered by temporal deadlines.
	F21	Social Trigger	Triggered by other people's actions/interactions (e.g., other family members' consumption behavior or diet).
			Not triggered by other people's actions/interactions.
	F22	More than one Trigger	More than one of the triggers mentioned above.
			Not more than one trigger.
Representation	F23	Digital Representation	Service delivery through the digital world (e.g., apps).
			No service delivery through the digital world.
	F24	Physical & Digital Representation	Service delivery through both worlds.
			No service delivery through both worlds.
Integration	F25	Integration into Ecosystem	Integration into an ecosystem of various other proactive services (e.g., the smart fridge can connect to other proactive services).
			No integration into an ecosystem.

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