Schmalenbach Journal of Business Research (2022) 74:345–387
https://doi.org/10.1007/s41471-022-00139-7

REVIEW ARTICLE

A Contextualized Acceptance Model for Proactive Smart Services

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Received: 6 September 2021 / Accepted: 11 August 2022 / Published online: 6 September 2022

Abstract Thanks to digital technologies, information about customer needs and contexts is becoming accessible ever more easily and service providers are more closely connected to customers. This development enables services to act on behalf of customers and to proactively initiate the customer interactions. Such services are so-called proactive smart services (PASS) and are a subgroup of smart services. Research suggests that service providers often face the challenge to gain customers' acceptance of innovative services. In response to this call for action and the change in customer interaction, which can have far-reaching consequences in the lives of customers, we examined the antecedents that explain customers' acceptance of PASS using a contextualized approach. Hence, we identified PASS-specific antecedents, developed a contextualized acceptance model (UTAUT2-PASS) while

This paper was originally submitted and independently peer-reviewed at Business Research, one of SBUR's predecessor journals. It has been accepted by the same Editor-in-Chief for publication in the successor journal SBUR.

Availability of data and material Not applicable

Code availability Not applicable

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drawing from general acceptance theory, and validated it empirically. A comparison of our contextualized model with UTAUT2 as an established yet uncontextualized model confirmed the outperformance of our contextualized model. Our findings advance the academic understanding of PASS and help service providers design PASS for customer acceptance.

Keywords Proactive Smart Services · Technology Acceptance · Factor Analysis · Contextualization

1 Introduction

Service plays a central role in global markets and is at the core of digital transformation (Alt et al. 2019; Beverungen et al. 2019b). In North America, Asia, and Europe, the service sector's GDP is about four times higher than for the industrial sector (Alt et al. 2019). Service entails interactive value co-creation through resource application and integration to the benefit of service providers and customers (Vargo and Lusch 2004). Traditionally, service involved interactions among customers and employees of service providers (Froehle and Roth 2004). In such interactions, customers typically make the first move, e.g., visiting a lawyer. Leyer et al. (2017) conceptualized this logic as "pull-" rationale. Yet, the nature of service is changing (Leyer et al. 2017; Huber et al. 2019; Barrett et al. 2015), as digital technologies enable service providers to capitalize on customer data and bridge the gap between the digital and physical world (Barrett et al. 2015; Larivière et al. 2017). Further, the Internet of Things (IoT) and advances in Artificial Intelligence (AI) foster new types of services which act on behalf of customers (Alt et al. 2019; Dreyer et al. 2019; Leyer et al. 2017) and change the service encounter by replacing service providers' employees with digital technologies (Froehle and Roth 2004; Larivière et al. 2017).

One of the most recent developments addressing the change in customer interaction has been the emergence of proactive smart services (PASS). PASS are a subgroup of smart services especially describing the autonomous and proactive behavior of smart services (Rau et al. 2020; Kabadayi et al. 2019; Porter and Heppelmann 2014). PASS are closely connected to digital technologies, enabling the continuous gathering of personal and contextual data from diverse sources (Hammer et al. 2015; Lee et al. 2012; Leyer et al. 2017). That way, PASS do not depend anymore on the customer to make the first move. Instead, they follow a "push-" rationale, where service providers leverage data on customer needs, daily routines, situational contexts, preferences, life events, as well as locations (Leyer et al. 2017; Linders et al. 2015). That way, PASS serve customer needs in an anticipatory and target-oriented manner through decision support and the performance of tasks on customers' behalf (Leyer et al. 2017).

Due to their novelty, little research is available regarding PASS in general and customers' acceptance of PASS. Recently, Rau et al. (2020) developed a multi-layer taxonomy of PASS' properties and conducted an empirical assessment of PASS examples in the business-to-consumer context. Thereby, they set PASS in relation to digital and smart services and identified that PASS are a subgroup—instead of representing a new type of service. With the taxonomy, researchers and practitioners can describe, classify, analyze, identify, and cluster PASS based on their properties. Regarding customers' acceptance of PASS, only Leyer et al. (2017) approached the topic from a customer perspective so far, testing the Reasoned Action Approach to identify antecedents explaining customers' digital PASS acceptance. Although their model fits the PASS context, Leyer et al. (2017) conducted a so-called "Level 1 contextualization" (Hong et al. 2014), contextualizing a general theory by adding or removing core antecedents that are context-specific but not directly connected to the properties of PASS. We argue that antecedents reflecting key properties of PASS enrich the understanding of PASS acceptance. Contextual properties are often unrecognized, unmeasured, or underappreciated, and thus, theory without accounting for contextual differences may lead to misapplication and reduce explanatory power (Hong et al. 2014). Missing contextualized insights into PASS acceptance may engender an improper design, customer dissatisfaction, and customer churn (Anderson et al. 2008). Further, smart services extend the value and efficiency of digital services (Fischer et al. 2020). In particular, the new developments in the change of customer interaction through services acting on behalf of customers and through the service-initiated interaction, all manifested in PASS, is worth investigating further in terms of customer acceptance. As the biggest challenges for service providers are the gain of customers' acceptance of innovative services (Wuenderlich et al. 2013, 2015), we investigate context-specific antecedents of PASS by following the guidelines of theory contextualization of Hong et al. (2014), yielding a "Level 2 contextualization." Our research question reads: *Which antecedents—especially PASS-specific antecedents—drive the acceptance of PASS in customer contexts?*

To address the research question, we propose a contextualized technology acceptance model for the PASS context (UTAUT2-PASS). This model provides insights into contextual antecedents, driving customers' willingness to accept PASS. A comparison with UTAUT2, an established yet uncontextualized model, confirmed our contextualized model's outperformance. Therefore, our work contributes to service research by deepening our understanding of PASS and specifying its design. The scientific value and contribution of contextualizing theories have been intensely discussed in research (e.g., Hong et al. 2014; Whetten 2009). Following these discussions, our key contribution refers to an improved understanding of the salient (and contextualized) antecedents affecting customers' acceptance of PASS. Thereby, the context-specific antecedents *Adaptability* and *Autonomy* have a significant effect.

Our work is organized as follows: In Sect. 2, we provide a theoretical background on service and technology acceptance models. In Sect. 3, we proceed by outlining our research method. We apply single-context theory contextualization to identify PASS-specific antecedents explaining customers' acceptance and to develop the UTAUT2-PASS model. In Sect. 4, we present analyses and results. In Sect. 5, we discuss the results by comparing the contextualized UTAUT2-PASS with UTAUT2. On this foundation, we offer theoretical and practical implications. We conclude by addressing limitations and by pointing to future research.

2 Theoretical Background

2.1 Smart Services and Proactive Smart Services

In service research, the singular term "service" reflects the process of using resources for the benefit of another entity. Conversely, the plural term "services" reflects a special type of output—an intangible product (Vargo and Lusch 2008). We use the terms in line with this reasoning: We refer to "service" when we mean the act of giving service to somebody. Conversely, we refer to "services" when we mean a variety or range of services, such as smart or PASS. The nature of service and how it is enacted has changed over the last decade (e.g., Barrett et al. 2015; Leyer et al. 2017; Riedl et al. 2010; Huber et al. 2019). Specifically, digital technologies offer novel means of value co-creation and lead to new types of services, such as smart services (Leyer et al. 2017; Barrett et al. 2015; Böhmann et al. 2004).

Smart services were initially interpreted as digital services delivered through smart products (Barrett et al. 2015; Beverungen et al. 2019a; Fischer et al. 2020). Regarding a smart service definition, two literature streams can be distinguished: In the first stream, *smartness* refers to dynamic adaptation, learning, and decision-making, all of which are enabled by extended data analysis and self-x capabilities (Barile and Polese 2010; National Science Foundation 2014). Data can be used for transactional purposes (e.g., collection, exchange, and storage) as well as for analytical (i.e., descriptive, diagnostic, predictive, and prescriptive) purposes (Want et al. 2015; Porter and Heppelmann 2014; Allmendinger and Lombreglia 2005). Analytical data usage enables basic self-x capabilities (e.g., self-monitoring and self-diagnosis) as well as extended self x-capabilities (e.g., self-optimization, self-configuration, and self-learning) (National Science Foundation 2014; Beverungen et al. 2019b). Hence, a smart service goal may refer to the anticipation and fulfillment of customers' needs (Kabadayi et al. 2019). In the second stream, *smartness* refers to smart things in value co-creation, which serve as boundary objects between the digital and the physical world (Beverungen et al. 2017, 2019b; Ouyang et al. 2017). Recently, Lim and Maglio (2018) reconciled both literature streams by defining smart service capable of learning, dynamic adaptation, and decision-making involving smart things. Such intermediaries facilitate customer data processing and data from the customers' environment (Kabadayi et al. 2019; Leyer et al. 2017; Hammer et al. 2015). We illustrate the evolution of smart services from a physical product dominated economy to a software and service-controlled economy through the influence of technology, data, and data analytics in Fig. 1. Thereby, the logic of smart services changed from preemptive (e.g., actions are based upon hard field intelligence to avert an undesirable event) to proactive (e.g., actions are based to predict future desires that customers do not even realize they might enjoy) (Allmendinger and Lombreglia 2005; Kabadayi et al. 2019; Leyer et al. 2017). The evolutionary demonstration in Fig. 1 is based on Porter and Heppelmann (2014) who differentiate smart services by their *Monitoring & Control, Optimization*, and *Autonomy* capabilities.

PASS are not a new type of service but a subgroup of smart services describing the highest evolution stage of this type of service (Rau et al. 2020). Thereby, PASS build on the properties of existing smart services from the *Monitoring & Control* and

		Definition	Fundamental properties	References
	Monitoring & Control	Smart services are services delivered to or through intelligent products that feature awareness and connectivity and resulted in benefits such as cost reductions, increased flexibility, increased access, and time savings.	• Smart products • Awareness • Connectivity • Preemptive • Basic self-x capabilities	• Allmendinger and Lombreglia (2005)
	Optimization	Smart services can be defined as services tailored to specific customer needs with the help of data and intelligent processing. It requires a deep understanding of customers and their particular contexts of use and an intelligent processing of these emergent data.	• Dynamic adaptation • Decision making • Ecosystem integration • Preemptive • Extended self-x capabilities	• Fleischer et al. (2014) • Medina-Borja (2015) • Porter and Heppelmann (2014) • Wuenderlich et al. (2015)
Proactive Smart Services	Autonomy	Smart services are personalized and pro-active services that are enabled by the integrated technology and intelligent use of data that can anticipate and fulfill customer needs at specific times and/or locations based on changing customer feedback and circumstances.	• Analytical-extended data usage • Proactive • Autonomous capabilities	• Beverungen et al. (2019) • Fischer et al. (2020) • Kabadayi et al. (2019) • Paukstadt et al. (2019)

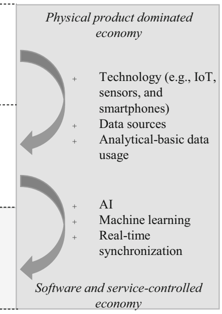

Fig. 1 Evolution of smart services

Optimization classification (e.g., use of intelligent intermediaries, use of different data sources, analysis of data, and adaption to changing input) but differentiate themselves by the fundamental properties proactivity and autonomy. PASS anticipate customers' needs before customers even know them and seamlessly provide decision support just-in-time, assist in the execution of a decision, or even decide and act on behalf of the customer (Leyer et al. 2017; Rau et al. 2020). To this end, PASS have the following concise properties:

Rationale In contrast to a traditional discrete demand setting, PASS always make the first move resulting in a substantial shift towards a business-initiated service co-creation. Leyer et al. (2017) refer to this logic as a "push-" rationale. Generally, customers need to configure PASS before the first usage. The configuration includes the use of data sources, the purposes of data usage, and the scope of action, combined with the degree of autonomy, which also affects all other fundamental properties (Lee et al. 2012). As a result, several PASS forms exist in the continuum between two poles but always realizing the "push-" rationale. The continuum stretches from customer-dependent to autonomous. Table 1 specifies the different forms with concrete examples of PASS applications.

The simplest form of PASS refers to recommender systems, still needing the most involvement of the customer. Thereby, the service primarily provides information or support customers' decisions by evaluating options using advanced analytics and is involved until the customer's decision or approval. Further, the PASS can act as a personal assistant via supporting decisions. However, the decision still lies with the customer. In the most sophisticated form, PASS refer to the state in which a customer's active involvement is not necessary, and PASS act on behalf of the customer by compiling alternate options, autonomously making decisions, and handling the enactment. Apart from the different forms, all PASS proactivity refers to the moment in which a value proposition is offered and takes place after the configuration phase and before customers are aware of their needs.

Data Source PASS leverage many different sources of personal (e.g., needs, preferences, or life events) and contextual data (e.g., circumstances, locations), which are combined to determine recommendations as well as to plan and execute ac-

Table 1 Concrete examples of PASS applications

No automation	Recommendation	Customer-approved decision	Autonomous decision
–	*Location recommender service:* This form of PASS provides recommendations for suitable restaurants to the customer at lunchtime. Thereby, the service relies on the nutrition goals or eating habits of the customer and contextual information like waiting times or details about restaurant menus	*Payment and return assistant:* This form of PASS is connected to the email inboxes and online shopping accounts of a customer. This may allow PASS to notify the customer about upcoming deliveries, return deadlines, and upcoming payments. PASS not only proactively inform the customer (e.g., upcoming payments) but also support his/her in the enactment (e.g., autonomous payment handling) after his/her decision (e.g., payment approval by the customer)	*Smart fridge:* The smart fridge as a PASS buys groceries while following customer's goals, preferences, and needs. It thereby adjusts the ordered products' quantity and quality concerning the customer's eating habits, preferred taste, holiday plans, and products' expiry dates. On behalf of the customer, this form of PASS initiates individualized groceries deliveries to the customer's home and handles respective payments while only updating the customer via push notifications on the smartphone

tions (Leyer et al. 2017; Linders et al. 2015). The special aspect of data source is that PASS also use information derived from everyday routines (Rau et al. 2020; Leyer et al. 2017). We understand the context as any information that can characterize a situation and thus is relevant to the interaction between the service and the customer (Dey 2001). Contextual data are not directly related to the customer but refer to a customer's environment (e.g., weather, geographical location), the product intended for the customer (e.g., information about supply chain partners, product availability), and additional open data sources (e.g., freely available government data) (Leyer et al. 2017; Kowalkiewicz et al. 2016).

Data Usage To ensure learning and decision-making, PASS base their function on integrating heterogeneous data sources and analysis capabilities. Thereby, PASS always have extended data analysis capabilities (i.e., diagnostic, predictive, and prescriptive) referring to the use of more sophisticated methods such as complex calculations, prediction models, machine learning, and comparable methods (Allmendinger and Lombreglia 2005; Porter and Heppelmann 2015; Want et al. 2015; Larivière et al. 2017). The PASS functioning strongly relies on the continuous analysis of customers' activities and data to identify or generate trigger events without customer interaction (Leyer et al. 2017). Triggers refer to internal and external stimuli that initiate a service-related action (e.g., proactive recommendation to the customer by PASS). These trigger events can be of any nature and do not solely rely on specific times or locations (Kabadayi et al. 2019).

Autonomy Moreover, PASS set up a comprehensive user model encompassing customers' preferences, goals, and activities. As these components are not static, PASS continuously update the user models and are expected to anticipate customers' behavior and reasoning based on past interactions and spontaneous behavioral changes (Chen and Popovich 2003; Kabadayi et al. 2019). Using the gathered data, PASS employ self-x capabilities to suggest, predict, or handle tasks to improve customers' efficiency and well-being (Leyer et al. 2017). To optimize user models, PASS offer different interaction possibilities to the customer: notifications, explanations, and feedback. Together, rich input data, self-x capabilities, and interaction permit a high degree of individualization and enable autonomous behavior, defining PASS as a subgroup from smart services (Leyer et al. 2017; Rau et al. 2020).

2.2 Technology Acceptance Models in a Service Context

Research on individual acceptance and use of technology is one of the most established and mature streams of information systems (IS) research (Venkatesh et al. 2016). Accordingly, extant research contains many technology acceptance models, which we classify as models concentrating on antecedents that either refer to 1) individual drivers, or 2) technical drivers of technology acceptance, or 3) hybrid models.

Examples of technology acceptance models that focus on technical drivers are the Technology Acceptance Model in various versions (TAM, for example, Davis 1989; Venkatesh and Davis 2000; Venkatesh and Bala 2008) with antecedents such as *Perceived Usefulness* or *Perceived Ease of Use*, the Model of PC Utilization (MPCU, Thompson et al. 1991) including antecedents such as *Affect, Complexity, Job Fit,* or *Long-term Consequences,* the Motivational Model (MM, Davis et al. 1992) with *Perceived Usefulness, Perceived Ease of Use,* or *Perceived Output Quality* as antecedents, and the Innovation Diffusion Theory (IDT, Moore and Benbasat 2001) with the exemplary antecedents *Relative Advantage, Comparability, Trialability* or *Image.*

Examples of technology acceptance models that focus on individual belief-based or emotional drivers are the Theory of Reasoned Action (TRA, Fishbein and Ajzen 1975) with antecedents such as *Behavioral Beliefs, Normative Beliefs,* or *Control Beliefs*, the Theory of Planned Behavior (TPB, Ajzen 1991) including antecedents such as *Attitude, Subjective Norm,* or *Perceived Behavioral Control*, and the Social Cognitive Theory (SCT, Compeau et al. 1999) with *Self Efficacy, Anxiety,* or *Outcome Expectations* as exemplary antecedents. Such models have their origins in psychology and sociology and aim at explaining behavior with beliefs about what one should do and the consequences of actions (Girod et al. 2017).

Finally, examples of hybrid models that combine the perspectives of the first two categories and respective antecedents are a model combining the TAM and the TPB (C-TAM-TPB, Taylor and Todd 1995), the Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al. 2003) with antecedents including *Performance Expectancy, Effort Expectancy, Social Influence*, or *Facilitating Conditions.* Its successor UTAUT2 includes new antecedents such as *Hedonic Motivation, Price Value*, or *Habit* and focuses on individuals' technology use in a customer context. UTAUT variants are specifically popular in the IS and other disciplines (Williams et al. 2012; Venkatesh et al. 2016). The literature also outlines that UTAUT is based on a high-quality theory (Venkatesh et al. 2012). The model explains 74% (52%) of the variance in individuals' behavioral intention of using a technology (of the variance in individuals' technology use) (Venkatesh et al. 2012). Also, academics argue that UTAUT has well-defined parts, a circumstance that is beneficial for our research. UTAUT—and, more specifically, UTAUT2—is considered as one of the most comprehensive technology acceptance models because it is brought about by distilling eight other models of technology acceptance that range from human behavior to computer science (Venkatesh et al. 2016).

While technology acceptance models flourished in the IS research, they have also been increasingly applied in service research. As technology also infuses service encounters and is the mean to improve customer service, technology acceptance models are applicable in service contexts. This circumstance is especially true for digital forms of service, with technology being at the heart of a service (Bitner et al. 2000; Venkatesh 2006).

In the literature, technology acceptance models have already been applied in the digital service field (Thong et al. 2011). To figure out whether existing research can directly be applied to PASS, being a subgroup of smart services, we conducted a structured literature review (Webster and Watson 2002; Vom Brocke et al. 2015).

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1 http://aisel.aisnet.org.

2 http://search.ebscohost.com.

3 http://www.sciencedirect.com.

Table 2 Results of the literature review

Acceptance theory	Service context	Source
Reasoned Action Approach	Digital proactive smart service	Leyer et al. (2017)
Own model	Digital home service	Noh and Kim (2010)
Own Model	Digital signage	Seol et al. (2013)
Own model	Mobile data service	Kim and Oh (2011)
Own Model	Self-service technology	Farah and Ramadan (2017)
TPB; UTAUT + TAM	Smart home service	Yang et al. (2017); Kim et al. (2017)
TAM	Digital health service	Schaarschmidt et al. (2017); Soroush et al. (2010)
TAM	Restaurant based e-service	Mozeik et al. (2009)
TAM	Digital shipping	Nikitakos and Lambrou (2007)
TAM	Human resource service	Huang and Martin-Taylor (2013)
TAM	Voice assistants	Coskun-Setirek and Mardikyan (2017)
TAM	Mobile shopping assistant service	Daraghmi (2016)
TAM + Protection Motivation Theory	Location-based service	Erskine et al. (2012)
TAM Own Model	Digital music service	Kwong und Park (2008); Sim et al. (2014)
TAM Own Model	Service of smart wearables	Kim and Shin (2015)
TAM + Privacy Calculus	Privacy dashboards	Cabinakova et al. (2016)
TAM + Technology Threat Avoidance Theory	Email authentication service	Herath et al. (2014)
TAM; UTAUT	Digital television	Sapio et al. (2010); Jung et al. (2009)
TAM; UTAUT	E-government service	Sipior et al. (2011); Venkatesh et al. (2011); Roy and Upadhyay (2017)
UTAUT	Digital-learning service	Pynoo et al. (2011)
UTAUT	Personal information and communication technology service	Thong et al. (2011)
UTAUT	Recommender system	Wang et al. (2012)
UTAUT + Divide Theory Innovation-Diffusion-Theory	Internet banking service	Dauda and Lee (2015); Gorbacheva et al. (2011); Pham and Ho (2015)
UTAUT Model of Adoption Technology in Households	Internet-based service delivery	Niehaves and Plattfaut (2014); Baltaci-Goktalay and Ozdilek (2010)
UTAUT2 + Extended Privacy Calculus Theory; TAM	IoT-based service	Weinhard et al. (2017); Liew et al. (2017)

We searched in the databases AISeL[1], EBSCOhost[2], and ScienceDirect[3], which gave us access to the top IS journals (i.e., Senior Scholar's basket of 8[4]) where technology acceptance research is an established research stream. Our search strings read (1) "Proactive," (2) "Service," (3) "Acceptance." The search strings were combined using the following logic: (1) AND (2) AND (3) in the title, abstract, or keywords. Search string (1) was also replaced by "Digital" or "Smart" to complete the literature review in the related subject areas (Rau et al. 2020).

This approach resulted in 358 scientific research articles corrected by duplications. The author team further examined the articles' content and classified them as relevant or irrelevant regarding the underlying research question. As soon as a mismatch arose within the author team concerning the classification of an article, the author team analyzed the concerned article in-depth until they reached a consensus regarding the classification. The following criteria were used to categorize a research article as relevant: An article either had to explicitly report antecedents contributing to the acceptance of mentioned types of services or employ an acceptance theory. Thereby, we excluded articles that do not focus on service and are not written in the customer context. The screening process resulted in 35 scientific research articles fulfilling at least one of the criteria mentioned above. Table 2 summarizes the results and shows that acceptance models are established in research on digital and smart services. Thereby, service contexts are quite diversified, ranging from digital home to healthcare, governmental, and banking services. Across the different contexts, however, it can be stated that TAM and UTAUT are established acceptance models in the service context.

3 Method

Recent research points to the proactivity and autonomy properties of PASS and argues, that existing technology acceptance models should be reflected on and set in context (Leyer et al. 2017; Rau et al. 2020). To develop a context-specific PASS acceptance model, we conducted the theory contextualization approach developed by Hong et al. (2014). As a central step, this approach adopts either an established or an emerging theoretical lens to guide the development of a context-specific model. Researchers adopting an established theoretical lens will encounter fewer challenges, particularly in explaining the theory's relevance to different contexts (Hong et al. 2014). Once a theoretical lens is adopted, two contextualization levels must be performed: Level 1 contextualization involves adding or removing core antecedents based on context. Thus, researchers may initially accept an existing general theory and decide to remove antecedents that do not suit the context or add antecedents to capture the context's facets at Level 1 (Hong et al. 2014). Level 2 contextualization involves finer contextualization efforts. Such efforts incorporate context-specific antecedents directly relevant to the properties of technologies, users, and the contexts of use (Hong et al. 2014; Whetten 2009).

[4] https://aisnet.org/?SeniorScholarBasket.

Table 3 Operationalization of guidelines for contextualization (Hong et al. 2014)

Activity	Guideline	Description	Summary	Justification of methodological avenue taken and details on operationalization
Identify a General Theory	1. Ground in a general theory	A general theory relevant to the domain of interest should be selected to guide the contextualization efforts	We adopted UTAUT2 to guide the development of a context-specific PASS model	The "Unified Theory of Acceptance and Use of Technology" (UTAUT) has been extensively used in research to explain human technology acceptance and use behavior (Venkatesh et al. 2016). UTAUT2 is specifically tailored to the customer context, corresponding to the PASS context (Venkatesh et al. 2012) When contextualizing such a theory for a certain context, such as PASS, the key question is whether the contextualization adds enough insights to justify the novel contextualized theory compared to using the more generalizable theoretical approach (i.e., UTAUT2). We will measure the contribution of the contextualized model by comparing it with the baseline model UTAUT2 in the following analyses. Specifically, we will compare the variance explained by each model and differences in the antecedents to challenge the degree of novelty of a contextualized model
Conduct Level 1 Context-ualization	2. Contextu-alize and refine general theory	A general model needs to be contextualized to the specific research domain	We refined UTUAT2 to the PASS context via conducting exploratory factor analysis (EFA)	A general model is not always generalizable to different IS contexts (Hong et al. 2014; Lee and Baskerville 2003). Thus, the refinement of the general model is necessary to include a minimal set of core antecedents relevant to the context researchers focus on. We refined the model by *removing* and *adding* core antecedents based on the context (Hong et al. 2014; Lee and Baskerville 2003). Removing antecedents aims at scale purification. It results in a contextualized UTAUT2 model with antecedents that best account for the variations and interrelationships of the manifest variables (Matsunaga 2010) To yield a contextualized UTAUT2 model, we first developed context-specific antecedents (see *Guideline 3* below) in addition to the already existing UTAUT2 antecedents. Second, we measured these context-specific antecedents by applying established guidelines for item development (Harrison und McLaughlin 1993; Hinkin 1998; MacKenzie et al. 2011; Tourangeau et al. 2000). We measured all items of the research model on a seven-point Likert scale. Third, we conducted an online survey on the crowdsourcing platform "Prolific" (https://prolific.ac) consisting of employees working in the service industry to collect data for the analysis. Finally, we performed an EFA on the data collected for all antecedents to identify which antecedents to add or remove

Table 3 (Continued)

Activity	Guideline	Description	Summary	Justification of methodological avenue taken and details on operationalization
Conduct Level 2 Contextualization	3. Identify context-specific antecedents	Context-specific antecedents can be identified based on past research or in-depth analysis using qualitative methods such as interviews or focus groups	We used a focus group of 12 German participants to examine contextual antecedents added to the refined general model (i.e., UTAUT2)	Different focus groups may be of interest in the context of PASS. Specifically, a practitioners-focused group would certainly be of great value. However, access to such practitioners fulfilling respective requirements (e.g., decision-makers of PASS) is not trivial. Thus, we used personal contacts and selected academic researchers with expertise in service research, digital life, or customer relationship management, like others researching acceptance (e.g., the acceptance of energy efficiency-related technologies, see Wunderlich et al. 2019; Venkatesh 2008). We anticipate that individuals who accept PASS will typically be employed in related fields. We also anticipate that participants will be potential adopters or current digital or smart services customers Our focus group comprised 12 German participants working on the following question: *What determines PASS acceptance?* We provided a PASS definition and two concrete examples (see Appendix A). Once a shared perception of PASS had been established, we moderated a discussion about PASS' key properties influencing acceptance
	4. Model context-specific antecedents	Context-specific antecedents are modeled	We modeled PASS context-specific antecedents	Hong et al. (2014) suggest examining overlaps and separable aspects of core and context-specific antecedents We examined these issues in the course of conducting EFA (see *Guideline 2* above). Specifically, we developed scales for all context-specific antecedents and examined the correlations of the measurement items of core and context-specific antecedents. Further, we formulated hypotheses for all antecedents

Table 3 (Continued)

Activity	Guideline	Description	Summary	Justification of methodological avenue taken and details on operationalization
	5. Examine the interplay between the IT artifact and other antecedents	Context-specific antecedents are included in the refined general model	We included the context-specific antecedents as direct predictors in the refined UTAUT2 model	Adding contextual variables as direct predictors of dependent variables is the most common option of contextualization in extant research (Bagozzi 2007; Hong et al. 2014) and one of the main types of UTAUT extensions (Venkatesh et al. 2016). Examinations of possible interactions among context-specific antecedents should be grounded in theory and provide theoretical insights into the contextualized model's mechanisms (Bagozzi 2007; Hong et al. 2014) Following this guideline, we applied structural equation modeling (SEM) to test our research model, more precisely PLS-SEM, because of the exploratory nature of our research (Hair Jr. et al. 2011). When validating the UTAUT2-PASS model, we again gathered data for the analysis from the crowdsourcing platform "Prolific."
	6. Examine alternative models	Different alternative models may be examined to better understand the phenomenon	Not applied	Previous *Guidelines* (1–5) yield theory-grounded models that mostly reveal the direct influence of context-specific antecedents on a phenomenon of interest. Hong et al. (2014) propose this step as optional when the researchers' objective is to examine indirect influences of context-specific antecedents Our objective refers to taking a first step in investigating how a contextualized version of UTAUT2 adds understanding to PASS. As we do not change the general theory UTAUT2 fundamentally, we do theory testing in the context of PASS. We take the theory UTAUT2 and investigate how a contextualized version of this theory adds an understanding to this phenomenon. We do not test for alternative models and leave this step for further research

To conduct theory contextualization, we followed the guidelines of Hong et al. (2014). Table 3 summarizes these guidelines and pinpoints the methodological avenues taken in this study. In the following, we state associated results.

4 Analysis and Results

4.1 Guideline 1: Ground in a General Theory

We adopt UTAUT2 as an established theory, guiding our development of a context-specific PASS acceptance model. In the discussion section, we will further measure the contribution of the contextualized model by comparing the contextualized model with the baseline model UTAUT2. Specifically, we will compare the variance explained by each model and differences in the antecedences to challenge the degree of novelty of a contextualized model.

4.2 Guideline 2: Contextualize and Refine General Theory & Guideline 3: Identify Contextualized Antecedents

These two guidelines represent the transition between Level 1 and Level 2 contextualization, and both refer to dropping and/or adding antecedents, which is why they are considered integrated in this study. Following Guideline 2, researchers may decide to remove antecedents which do not suit the context (Hong et al. 2014). Further, following Guideline 3, researchers may decide to add context-specific antecedents reflecting properties of technologies, users, and contexts (Hong et al. 2014; Whetten 2009). We first searched for new context-specific antecedents to be added to the model and therefore started with Guideline 3. After having a rich pool of antecedents, we conducted an EFA to evaluate which antecedents to drop and which ones to keep, representing Guideline 2.

As stated in Table 3, we used a focus group to identify context-specific antecedents. The discussion in the focus group was primarily on the key property ‘autonomy.’ Starting from this key property, the process brought further discussions and questions forward, that arise from an ‘autonomy’ rationale, such as the probability of losing control over PASS. Based on the discussions in the focus group and our field notes, the author team discussed and reflected on the content and derived context-specific antecedents of PASS acceptance. This resulted in four context-specific antecedents: The antecedents *Autonomy* and *Reversibility* were directly transferred from the discussions in the focus group to our research model since they were concrete and clearly measurable. Two further antecedents (i.e., *Adaptability* and *Trust*) were quite broadly discussed in the focus group. Hence, it was our task then to set them in context, interpret them, and develop so-called “root-antecedents.” The concept of root antecedents was initially suggested by Venkatesh et al. (2003) when developing UTAUT: While core antecedents represent an overarching principle, root antecedents reflect specific domains of core antecedents. Table 4 summarizes the reasoning of authors, the antecedents and (if applicable) their respective root antecedents.

Table 4 Context-specific antecedents

Antecedent	Reasoning of authors why the antecedent might be included (based on reflections of focus group input)	(If applicable) root antecedent	Definition
Adaptability	PASS need various ways and degrees of freedom to adapt to customer preferences and to successfully act on behalf of them. So, without adaptability, a PASS cannot unfold its full autonomy potential or at least not in line with customers' dynamically changing preferences	NA	Adaptability describes the extent to which a service can be adapted to the changing demands of customers or circumstances
		Individualization	Individualization describes the extent to which a service identifies customers' preferences and goals at a high degree of individualization by collecting and analyzing data on customer patterns. Furthermore, the service interprets customers' everyday activities and derives predictive behavior
		Interaction	Interaction refers to the extent to which customers can participate in modifying the format and content of a mediated environment or transactions in real-time and give feedback
		Context Awareness	Context Awareness describes the extent to which a service can adapt to changing environmental circumstances
Autonomy	The key feature of PASS differentiating it from 'ordinary' smart services is the autonomy feature. Thus, this feature may have a substantial influence on customers' acceptance of PASS	NA	Autonomy describes the execution of tasks or decisions on behalf of a customer and without a human trigger

Table 4 (Continued)

Antecedent	Reasoning of authors why the antecedent might be included (based on reflections of focus group input)	(If applicable) root antecedent	Definition
Reversibility	The autonomous behavior of PASS might trigger questions about reversibility in cases of mistakes caused by the PASS (e.g., ordering too much or the wrong items). Thus, the question of whether actions of the PASS are reversible is likely an essential one for acceptance	NA	Reversibility describes the risks involved in decisions or actions, and the possibility of reversing them
Trust	The autonomous behavior of PASS might trigger questions about the probability of losing control over PASS and associated consequences. Thus, being able to trust a PASS, especially if the service acts autonomously, is likely an essential for acceptance	NA	Trust describes a subjective belief that a party will fulfill their obligations and plays an important role in uncertain situations where customers of the systems are vulnerable
		Trust in Service	*Trust in Service* refers to customers' belief that a service will be provided in line with their expectations, and customers' willingness to disclose private information in order to access all functionality of a pervasive application
		Trust in Service Provider	*Trust in Service Provider* describes the extent to which customers believe that selling parties keep their promises and ensure data privacy and security. It determines whether the customer will maintain a relationship with the provider in the future, as well as the future value of the relationship

NA Not Applicable

As stated in Table 3 above, we conducted EFA to develop measurement scales for our context-specific antecedents (see Appendix B). To measure the eight UTAUT2 antecedents, we applied the original items determined by Venkatesh et al. (2012).

The survey conducted to collect data for the EFA included 260 respondents (118 females), and with a mean age of 31 years. There was no evidence of any systematic bias in the survey that could have caused premature abandonment. We tested for nonresponse bias, comparing early- and late-respondents using a late-respondent proxy for a non-respondent (Armstrong and Overton 1977). Since all of the questions were mandatory, we obtained a data set without missing values. To address common method variance (CMV), we used *a priori* remedies and *post hoc* detection methods. *A priori* remedies included guaranteeing anonymity during the data collection process, assuring the participants that there are no true or false answers, and asking the participants to give honest, carefully worded answers and scaling the developed items (Podsakoff et al. 2003). For *post hoc* detection methods, we applied the correlational marker technique (Lindell and Whitney 2001) and the confirmatory factor analysis marker technique (Richardson et al. 2009). Both assessments indicated the absence of CMV in our sample.

With an item-to-response ratio 1:5, the sample was sufficiently large for an EFA, which we conducted next (MacKenzie et al. 2011). EFA serves to refine the quality of the measurement scales developed for the twelve antecedents and examine their respective scale properties and reliability. In this analysis, we tested for the antecedent structure that underlies the items. The number of antecedents that need to be extracted was determined by applying a parallel analysis (Horn 1965). We applied "promax" rotation to extract the oblique antecedents and identify potential antecedents' correlation (Costello and Osborne 2005).

The EFA suggested nine (instead of the theorized twelve) core antecedents extract with loadings of 29 (instead of the theorized 48) items. We excluded items with a major loading lower than the conventionally accepted threshold of 0.60 (Ford et al. 1986; Gefen and Straub 2005; Urbach and Ahlemann 2010). The principle of the scale purification and antecedent refinement process is the deletion of sub-dimensions, indicating that all the essential aspects of the core antecedents are captured by the remaining dimensions (MacKenzie et al. 2011). Cronbach's Alpha values were higher than 0.75 for all of the remaining antecedents, which indicated reliable remaining antecedents and, in particular, internal consistency and content validity (Robinson et al. 1991). Table 5 summarizes the item loadings and the antecedents' Cronbach Alpha values. Please note that we dropped items marked grey with an asterisk due to loadings below 0.60, as stated above.

We now interpret the resulting nine core antecedents based on their respective items: first, *Adaptability* consists of the two root antecedents *Individualization (IND)* and *Context Awareness (CA)*. For the potential third root antecedent *Interaction* (INT) loadings are excluded as they were below the defined threshold. Second, the antecedent *Trust* consists of the root antecedent *Trust in Service Provider (TS)* (Palvia 2009; Singh and Matsui 2017). As the other root antecedent *Trust in Service* did not indicate major loadings for this antecedent, we dropped it. Third, the items of *Autonomy* load on two antecedents. We, therefore, introduced a novel antecedent entitled *Controllability*. In our definition, PASS exist in the continuum between two

Table 5 Main loadings and cross-loadings resulting from EFA

Item ID								Antecedents		Cronbach's Alpha
	1	2	3	4	5	6	7	8	9	
IND_01[a]	0.55	0.04	0.23	–0.02	0.00	0.14	0.05	0.09	–0.07	0.91
IND_02	0.60	0.02	0.12	0.11	0.01	0.05	0.09	0.04	0.10	
IND_03	0.65	0.00	0.24	–0.07	–0.05	0.09	0.12	0.01	–0.11	
INT_01[a]	0.34	0.09	0.19	0.02	–0.07	0.13	0.03	0.14	0.14	
INT_02[a]	0.47	0.32	0.05	0.10	0.15	0.00	–0.04	0.02	0.08	
INT_03[a]	0.46	0.35	0.01	0.07	0.20	0.02	–0.09	0.00	0.08	
CA_01[a]	0.50	0.04	–0.11	0.04	0.14	–0.02	0.05	0.11	0.23	
CA_02[a]	0.58	–0.06	–0.02	0.04	0.14	–0.03	–0.01	0.11	0.13	
CA_03	0.60	–0.14	0.06	–0.04	0.10	–0.03	0.10	0.11	0.04	
CA_04	0.65	0.00	–0.17	–0.04	–0.02	0.03	0.12	0.05	0.14	
TS_01[a]	0.23	0.07	0.36	–0.30	0.16	0.12	0.01	–0.01	0.04	[b]
TS_02[a]	0.23	0.23	0.17	–0.30	0.16	0.00	0.13	0.07	0.13	
TS_03[a]	0.18	0.20	0.21	–0.26	0.22	–0.02	0.12	–0.03	0.04	
TP_01	–0.04	0.84	0.01	–0.02	0.01	0.04	0.01	0.05	–0.01	0.94
TP_02	–0.07	0.74	0.03	0.10	–0.03	0.04	0.08	–0.05	0.15	
TP_03	0.03	0.92	–0.03	–0.03	–0.05	–0.01	0.01	0.00	0.04	
TP_04	–0.01	0.92	–0.03	0.04	–0.03	0.00	0.01	0.03	0.00	
AU_01	0.06	–0.07	0.77	0.07	0.03	–0.04	0.04	–0.01	0.04	0.84
AU_02	0.02	–0.03	0.67	0.03	0.02	0.01	0.10	0.09	–0.02	
AU_03	0.03	0.16	0.02	0.70	0.06	0.02	0.01	0.03	0.08	0.76
AU_04	0.03	0.01	0.15	0.68	–0.04	0.04	0.07	0.07	0.06	

Table 5 (Continued)

Item ID								Antecedents		Cronbach's Alpha
	1	2	3	4	5	6	7	8	9	
RE_01[a]	0.10	0.34	0.00	0.37	0.17	–0.01	–0.08	–0.03	–0.02	[b]
RE_02[a]	0.11	0.36	–0.11	0.28	0.12	0.11	–0.12	–0.07	0.08	
PE_01	–0.04	–0.02	0.07	0.04	0.73	0.18	0.01	0.02	0.01	0.93
PE_02	–0.04	–0.01	0.09	–0.04	0.74	0.00	0.12	0.06	0.03	
PE_03	0.01	0.00	–0.02	–0.01	0.79	0.03	0.05	0.02	0.07	
PE_04	0.10	–0.06	–0.08	–0.03	0.76	–0.07	0.13	0.03	0.16	
EE_01	0.01	0.05	0.03	0.03	0.02	0.80	–0.04	0.03	0.03	0.93
EE_02	0.02	0.07	–0.09	0.00	0.03	0.80	0.06	0.01	0.03	
EE_03	–0.06	–0.03	0.02	0.06	0.02	0.83	–0.01	–0.01	0.10	
EE_04	0.01	–0.05	0.01	–0.05	–0.04	0.89	0.04	0.02	0.08	
SI_01	0.00	–0.02	0.04	0.04	0.00	0.01	0.89	0.01	0.01	0.95
SI_02	–0.02	0.02	–0.02	–0.02	–0.01	0.01	0.98	–0.04	0.01	
SI_03	0.03	0.01	–0.02	0.03	0.03	0.00	0.90	0.04	–0.04	
FC_01[a]	0.11	0.06	0.12	–0.01	0.45	0.26	0.09	0.03	–0.19	[b]
FC_02[a]	0.18	0.10	–0.08	0.06	0.47	0.35	0.04	–0.01	–0.16	
FC_03[a]	0.23	0.13	–0.14	–0.04	0.35	0.27	0.09	0.00	–0.12	
FC_04[a]	0.25	0.12	0.11	0.02	0.29	0.08	0.02	0.07	–0.02	
HM_01	0.03	0.01	0.01	0.02	–0.06	0.00	–0.01	0.93	0.01	0.94
HM_02	–0.02	0.04	–0.02	0.02	0.03	0.04	–0.03	0.90	–0.02	
HM_03	0.00	–0.05	–0.03	0.02	–0.01	–0.01	0.02	0.96	0.00	

Table 5 (Continued)

Item ID	Antecedents									Cronbach's Alpha
	1	2	3	4	5	6	7	8	9	
PV_01	–0.02	0.06	0.01	–0.05	–0.04	0.14	0.00	0.00	0.77	0.93
PV_02	0.00	0.01	0.02	0.08	0.09	0.04	–0.01	–0.01	0.83	
PV_03	0.07	0.05	–0.01	0.01	0.01	0.07	0.00	0.00	0.85	
HT_01[a]	–0.02	0.15	0.31	–0.23	0.27	–0.03	0.10	0.23	0.00	[b]
HT_02[a]	–0.03	0.07	0.27	–0.30	0.13	–0.09	0.11	0.29	0.01	
HT_03[a]	0.04	0.14	0.17	–0.27	0.31	0.02	0.21	0.17	0.08	
HT_04[a]	0.07	0.03	0.10	–0.30	0.27	0.04	0.10	0.27	0.09	

IND Individualization, *INT* Interaction, *CA* Context Awareness, *TS* Trust in Service, *TP* Trust in Service Provider, *AU* Autonomy, *RE* Reversibility, *PE* Performance Expectancy, *EE* Effort Expectancy, *SI* Social Influence, *FC* Facilitating Conditions, *HM* Hedonic Motivation, *PV* Price Value, *HT* Habit

[a]Items excluded, due to loading <0.6

[b]Cronbach Alpha value not applicable, because we excluded antecedent and respective items

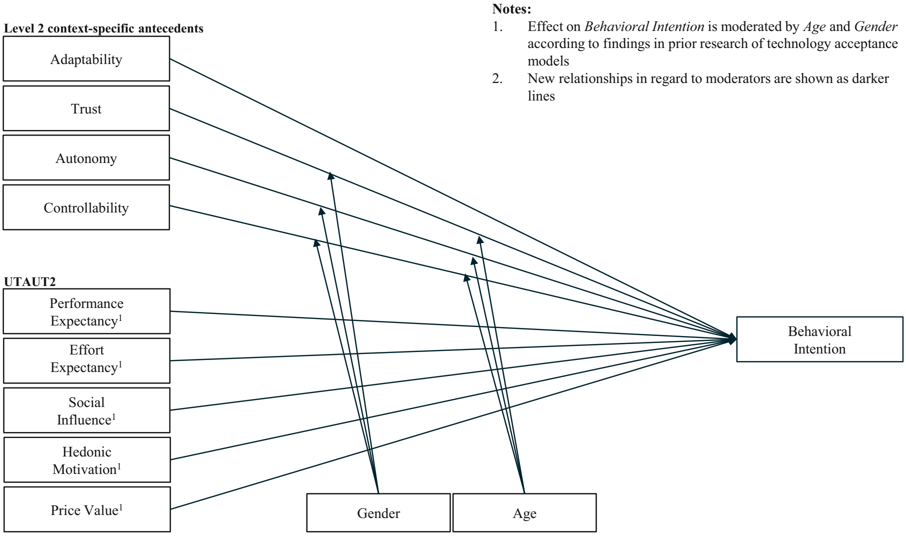


Fig. 2 Research model UTAUT2-PASS

poles—customer-dependent and autonomous—for configuration. From a content perspective, the *Autonomy* items cover the autonomous configuration (i.e., service acts on behalf of the customer), and the items of *Controllability* cover the customer-dependent configuration of PASS. Finally, the antecedents *Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation,* and *Price Value* characterized and confirmed the research results of UTAUT2 (Venkatesh et al. 2012).

Concerning the antecedents dropped, the loadings of *Reversibility, Facilitating Conditions*, and *Habit* were below the defined threshold. *Reversibility* describes the risk involved in decisions or actions and the possibility of reversing these (Davis et al. 1995; Heal 1977; Moorthy and Srinivasan 1995). We suggest that *Reversibility* is dropped because we gathered data for PASS in general and did not distinguish between PASS forms. In customer-dependent configurations, the customers are always in control, and a low level of risk is involved. Consequently, the ability to reversing one's decision is not needed or favored by customers. *Facilitating Conditions* does not function as a good antecedent for new technologies if uncertainties are involved (Ajzen 1991; Sheeran et al. 2003; Venkatesh et al. 2008). Customers do not usually consider which resources and knowledge are needed to use the technology or service when it comes to detail. This circumstance origins from the low adoption rate of PASS. Ultimately, the items of *Habit* also do not have a major loading on one antecedent. Since *Habit* depends on prior experiences and on the degree of familiarity that is developed with a target technology or service, the novelty, as well as the participants' non-usage of PASS, means that they cannot fulfill these conditions (Kim and Malhotra 2005; Limayem et al. 2007; Brauer et al. 2016). As a result, the participants cannot make any statements about their *Habit*.

4.3 Guideline 4: Model Context-Specific Antecedents

As stated in Table 3 above, we formulate our contextualized PASS acceptance model. Fig. 2 captures this model. In the following, we discuss each antecedent's relevance and formulate hypotheses that refer to customers' *Behavioral Intention* to accept PASS. Please note that *Use Behavior* as a dependent variable is not part of UTAUT2-PASS. This is due to PASS' properties and the fact that diffusion has just begun, and, despite strong growth, the adoption rate is still low. Further, we adopted the original moderators *Age* and *Gender* from the UTAUT2 but did not include *Experience*, again because of the novel diffusion of PASS.

Adaptability *Adaptability* (AD) encompasses the root antecedents *Individualization* (IND) and *Context Awareness* (CA). We hypothesize that the level of *Adaptability* influences PASS acceptance as customers might expect PASS to provide customer suggestions and decisions and to adapt to modifications of preferences, goals, or circumstances (Ziefle et al. 2011; Bobadilla et al. 2013; Hammer et al. 2015; Leyer et al. 2017). If the level of *Adaptability* is high, PASS improve in quality by providing customized service (Gura et al. 2001). We, therefore, postulate that:

H1: Adaptability has a positive effect on customers' Behavioral Intention to use PASS.

Trust *Trust* (TR) is comprised of the root antecedent *Trust in Service Provider* (TP) (McKnight et al. 2002; Hammer et al. 2015). We conjecture that *Trust* influences PASS acceptance because PASS lack face-to-face interactions and can operate without human intervention (Hammer et al. 2015; Singh and Matsui 2017). Thus, customers may not always understand PASS' actions, and that way, they have to trust that PASS will fulfill their obligations, especially if PASS decide autonomously (Singh and Matsui 2017; Hammer et al. 2015). Accordingly, *Trust* can be a central requirement of customers' PASS acceptance (McKnight et al. 2011), and we postulate:

H2: Trust has a positive effect on customers' Behavioral Intention to use PASS.

Impact of Trust Moderated by Age and Gender We expect that *Age* and *Gender* (GDR) moderate the relationship between *Trust* and *Behavioral Intention*. Previous studies suggest that men are more trusting than women because women perceive a greater risk (i.e., privacy concerns) and have more psychological barriers to building trust (Sheehan 1999; Rodgers and Harris 2003; Buchan et al. 2008; Riedl et al. 2010). Moreover, older customers value trust more highly and strongly rely on well-known and established brands, whereas the younger generation only relies on the available information if they can judge the trustworthiness of a service (Rouibah et al. 2008; Deng et al. 2010; Hoffmann 2012). We, therefore, postulate that:

H3: Age and Gender will moderate how Trust affects Behavioral Intention such that the effect will be stronger among women—particularly older women.

Autonomy and Controllability We conjecture that *Autonomy (AU) and Controllability* (CO) influence PASS acceptance because PASS can take in different forms. *Autonomy* covers the autonomous configuration (i.e., the task is carried out without a customer's final agreement, and the permission was conferred long ago). *Controllability* covers the customer-dependent configuration of PASS, or, in other words, the management, controlling, and governance of the service (i.e., the final decision is incumbent upon the customer and the permission was not conferred long ago). These proactivity forms are appropriate for different tasks and in different contexts, depending on the associated sensitivities or complexity and the customers' attitudes (Leyer et al. 2017). We, therefore, postulate that:

H4: Autonomy has a positive effect on customers' Behavioral Intention to use PASS.

H5: Controllability has a positive effect on customers' Behavioral Intention to use PASS.

Impact of Autonomy and Controllability Moderated by Age and Gender We expect *Age* and *Gender* to moderate the effects that *Autonomy* and *Controllability* have on *Behavioral Intention*. Men tend to make decisions, even risky ones, based on selective information and heuristics, while women tend to reflect and seek more information when making decisions (Bakan 1966; Deaux and Lewis 1984; Schubert et al. 1999). Moreover, older customers tend to feel less empowered to make their own decisions and, consequently, be grateful to relinquish their active decision-making role (Levinson et al. 2005; Chen and Chan 2011). Since *Autonomy* involves risk and convenience and *Controllability* involves safety and governance for customers, we postulate that:

H6: Age and Gender will moderate how Autonomy affects Behavioral Intention such that the effect will be stronger among men—particularly older men.

H7: Age and Gender will moderate how Controllability affects Behavioral Intention such that the effect will be stronger among women—particularly younger women.

For the remaining UTAUT2 antecedents, we adopted the hypotheses of Venkatesh et al. (2012).

4.4 Guideline 5: Examine the Interplay Between the IT Artifact and Other Antecedents

As stated in Table 3 above, we applied SEM to test our research model. We measured the dependent antecedent *Behavioral Intention* as suggested by Venkatesh et al. (2012), the moderators *Age* in years, and the moderator *Gender* as a dummy variable, with 1 representing women.

The survey to collect data, included 307 respondents (138 women) with a mean age of 33 years. With an item-to-response ratio higher than 1:10, the sample was sufficiently large to conduct a SEM (MacKenzie et al. 2011). As in our first survey, there was no evidence of any systematic bias that could have caused premature abandonment. Since there were no statistically significant differences in early- and late-respondents' demographic characteristic, we could exclude nonresponse bias

Table 6 Descriptive statistics: correlations and AVEs

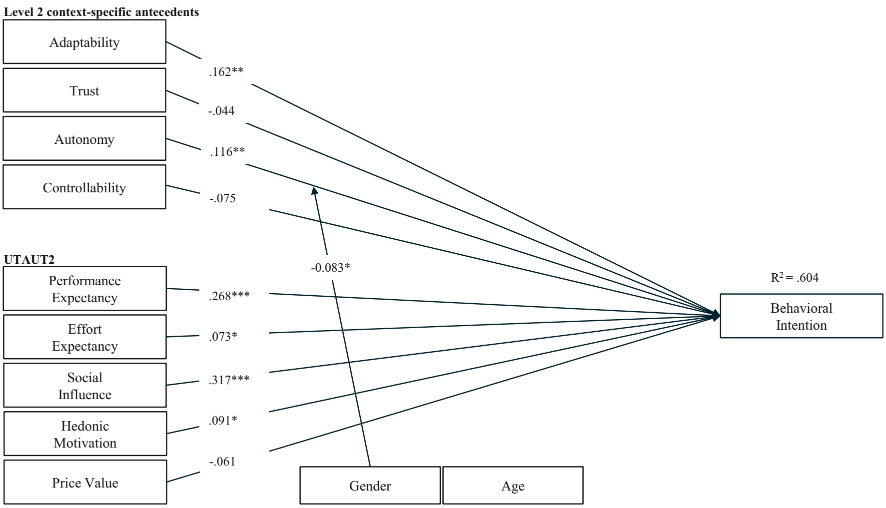
	Descriptive Statistics			Correlations											
	ICR	MN	SD	AD	TR	AU	CO	PE	EE	SI	PV	HM	BI	Age	GDR
AD	0.881	0.161	0.068	**0.855**	–	–	–	–	–	–	–	–	–	–	–
TR	0.946	–0.037	0.066	0.143	**0.866**	–	–	–	–	–	–	–	–	–	–
AU	0.881	0.114	0.051	0.457	0.008	**0.946**	–	–	–	–	–	–	–	–	–
CO	0.78	–0.071	0.058	0.004	0.470	–0.115	**0.866**	–	–	–	–	–	–	–	–
PE	0.918	0.276	0.065	0.555	0.163	0.356	0.104	**0.896**	–	–	–	–	–	–	–
EE	0.910	0.071	0.056	0.484	0.352	0.229	0.198	0.573	**0.886**	–	–	–	–	–	–
SI	0.950	0.313	0.060	0.461	–0.098	0.436	–0.139	0.494	0.245	**0.953**	–	–	–	–	–
PV	0.954	0.062	0.054	0.303	0.352	0.140	0.232	0.414	0.529	0.132	**0.956**	–	–	–	–
HM	0.924	0.087	0.054	0.371	–0.035	0.249	–0.036	0.394	0.219	0.480	0.169	**0.932**	–	–	–
BI	0.965	–	–	0.546	–0.053	0.476	–0.132	0.595	0.362	0.654	0.179	0.444	**0.983**	–	–
Age	1.000	0.007	0.043	–0.057	0.068	–0.048	–0.039	–0.097	0.018	–0.108	0.023	–0.010	–0.070	**NA**	–
GDR	1.000	0.052	0.038	0.038	–0.086	0.149	–0.071	–0.008	–0.054	0.131	–0.097	0.071	0.130	–0.065	**NA**

Diagonal elements represent AVEs and off-diagonal elements correlations
AD Adaptability, *TR* Trust, *AU* Autonomy, *CO* Controllability, *PE* Performance Expectancy, *EE* Effort Expectancy, *SI* Social Influence, *PV* Price Value, *HM* Hedonic Motivation, *BI* Behavioral Intention, *GDR* Gender, *ICR* Internal Consistency Reliability, *MN* Mean, *SD* Standard Deviation

(Armstrong and Overton 1977). We again applied a priori remedies and post hoc detection methods to address CMV, indicating that CMV is absent. Further, to address multicollinearity, we examined the correlation table and the variance inflation factor (VIF) values of the latent antecedents. We found that the VIFs were approximately 1.66, with a maximum of 2.36 (see Appendix C). The values were less than the critical threshold of five and far less than the conservative threshold of ten (Gefen et al. 2000). Thus, multicollinearity was not a critical issue in our results.

Table 6 states the internal consistency (ICRs) of all antecedents. ICR values above the recommended threshold of 0.70 indicate high internal consistency (Gefen et al. 2000). The average variance extracted (AVE) of all antecedents was above 0.50 and exceeded the individual highest square correlations of any other latent antecedent (Fornell and Larcker 1981). Further, the values of the heterotrait-monotrait ratio of correlations (HTMT) were below the recommended threshold of 0.90 (see Appendix C). These outcomes support convergent and discriminant validity (Henseler et al. 2015; Hair Jr. et al. 2016).

We used SEM to analyze two separate models. The first model included no moderator or, more precisely, displayed only the direct effects (labeled "D only"). The second model included all moderators, namely the individual interaction terms (labeled "D + I"). The adjusted R^2 reflects the models' fit. Fig. 3 presents the results of predicting customers' *Behavioral Intention* and including the direct effects and individual interaction terms. Further, all significant antecedents affect R^2 according to their f^2 scores (see Appendix C). Thereby, the context-specific antecedents *Adapt-*



Notes:

1. ****p < .01: **p < .05; *p < .1.*
2. For the sake of clarity, we omit insignificant path coefficients of moderators *Age* and *Gender*

Fig. 3 Results of the UTAUT2-PASS

ability and *Autonomy* have a medium effect on R^2 underlying their importance in our contextualized model.

As illustrated in Fig. 3, our findings confirmed the antecedents based on traditional technology acceptance models, except for the antecedent of *Price Value*. When we included interaction terms, we also found a significant path coefficient with higher-order interaction terms, such as *Autonomy* × *Gender*, when we predicted *Behavioral Intention*. A slope analysis revealed that the relationship between *Autonomy* and *Behavioral Intention* is stronger for men. Moreover, UTAUT2-PASS explains significant variance in *Behavioral Intention,* indicating 56.6% for direct effects and 60.4% for moderated effects. Overall, the results support our antecedents' applicability and validity or determining customers' behavioral intentions for PASS based on a widely accepted significance level of 10% for exploratory studies (Hair Jr. et al. 2016). Accordingly, our hypotheses H1 and H4 are fully supported. Hypotheses H6, which holds that *Age* and *Gender* will moderate how *Autonomy* affects *Behavioral Intention*, is supported to a certain extent in that only *Gender* is found to be significant. To better interpret and discuss our contextualized model results, we further conduct a survey validating the original UTAUT2 (Level 1 contextualization) applied in the PASS context and compare the results with those of our UTAUT2-PASS model (Level 2 contextualization). We focus on the comparison and highlight the contextualized antecedents' role in more detail in the following section.

4.5 Guideline 6: Examine Alternative Models

As elaborated in Table 3 above, we did not apply this (optional) guideline.

5 Discussion

So far, little research has been conducted on accepting service with a "push-" rationale. This study builds upon UTAUT2, which guides our contextualization efforts. Overall, our contextualized UTAUT2-PASS model is likely to inspire research on other service featuring a "push-" rationale and autonomy. Thereby, our contextual antecedents can inform service providers regarding PASS design.

Before reflecting on the results in detail, we performed a robustness check. This check serves for highlighting the relevance of our contextualized UTAUT2-PASS model and its outperformance. To this end, we conducted another survey by just validating the original UTAUT2 in the PASS context. This comparison enabled us to better understand our results and our finer contextualization approach's value and importance. Therefore, we applied the original items determined by Venkatesh et al. (2012). The sample included 227 respondents (83 women) with a mean age of 31 years. As in our prior surveys, we validated the original UTAUT2 model with SEM and checked for any systematic bias, nonresponse bias, multicollinearity, internal consistency, and conducted further validity tests. These measures did not reveal any issues, and the results can be found in a separate report (see Appendix D). When comparing the results of UTAUT2 and UTAUT2-PASS, we identified similarities in the significance of the antecedents *Performance Expectancy, Effort Expectancy*, and *Social Influence*.

What is more, *Performance Expectancy* and *Social Influence* are the strongest antecedents in both models. This is in line with the findings of Leyer et al. (2017). The uncontextualized UTAUT2 model exhibits no further significant antecedents, and no moderator influences the independent variables. In contrast, our model exhibits more significant antecedents (i.e., *Hedonic Motivation, Adaptability, and Autonomy*). Moreover, the moderator *Gender* influences customers' *Behavioral Intention*. Accordingly, there are no contradictions regarding the significant antecedents of both models, and the results of UTAUT2 corroborate our decision to eliminate *Facilitating Conditions* and *Habit*. Hence, our model is not a simple extension of UTAUT2, as we added PASS-specific antecedents and eliminated established antecedents that did not fit the PASS context according to Guideline 2 of Hong et al. (2014). This improvement is reflected in the model fit (Adjusted R^2) of our contextualized model explaining 60.4% of the variance since UTAUT2 only explains 35.7%. In conclusion, the comparison attests that our contextualized model is more appropriate regarding the acceptance of PASS than an established general theory (i.e., UTAUT2).

Generally, results allow us to derive the following theoretical and managerial implications: To start with the theoretical implications, results reveal the relevance of some antecedents from general technology acceptance theory in the PASS context, namely *Performance Expectancy, Effort Expectancy, Social Influence*, and *Hedonic Motivation. Price Value* does not significantly influence the intention to use PASS. We can explain this lack of significance in terms of customers' deficient insights and understanding of related prices and costs (Zeithaml 1988) or customers' inability to consider *Price Value* as a criterion for PASS (Kim et al. 2004; Hu et al. 2009). As far as the moderators are concerned, we highlighted that *Gender* has a moderating effect on the antecedents, whereas *Age* is not relevant in the PASS context.

Second, as summarized in Appendix B above, we developed new antecedents that reflect PASS' key properties (i.e., *Adaptability, Trust, Autonomy*, and *Controllability*), which might be harnessed in future research. Developing these antecedents differentiates our work from extant literature in the field: For example, we are so far the first analyzing the effect of a dedicated *Autonomy* antecedent on acceptance of PASS. Extant literature could not investigate such dedicated antecedents reflecting PASS properties, as they 1) used established models to measure PASS acceptance which did not account for these antecedents (e.g., Leyer et al. 2017) or 2) investigated related concepts, that only touch on 'autonomy' and thus only measured facets of it (e.g., "*Control Beliefs*" or "*Self-Efficacy*" in Leyer et al. 2017, or "*Automation*" in Yang et al. 2017). Taking a more nuanced view, while also accounting for other, more established antecedents, showed adequate validity in our model and might offer avenues to deepen the research in future.

Third, we analyzed the impact of these new antecedents on customers' behavioral intention to use PASS. The results imply that *Adaptability* has a direct impact. In contrast, *Trust* does not affect customers' behavioral intention to use PASS—although one could have assumed that trust is essential since PASS deal with personal data. In the context of data sharing, Morey et al. (2015) and Bertoncello et al. (2016) point out that 79% of customers are positively influenced by disclosing personal data—even non-required data—when receiving special offers, data-enabled benefits, or being assisted with complex decisions. The paradox is that customers are most sensitive to personal data, and yet customers are most willing to share personal data if they expect to receive value-adding service in return (Gimpel et al. 2018; Bertoncello et al. 2016; Morey et al. 2015). This phenomenon is called privacy paradox and can be explained by trust in the service provider, lack of risk awareness, lack of knowledge about privacy-friendly behaviors, or social benefits of self-disclosure (Ebbers et al. 2021; Hargittai and Marwick 2016; Kokolakis 2017). In particular, 'digital natives' are more accustomed to providing personal data (Prensky 2001). Younger customers also seem to perceive risks differently from older customers, and they—even when perceiving greater risks, they not necessarily change their behavior or attitudes (Quint and Rogers 2015). On this basis, we suppose that *Trust* does not function as an antecedent: Due to the strong influence of *Performance Expectancy*, customers have a high expectation of the benefits when using PASS that potentially outweighs any trust concerns, yielding the privacy paradox.

Furthermore, *Autonomy* and *Controllability* are two important antecedents. While *Autonomy* covers the autonomous configuration of PASS, *Controllability* relates to the customer-dependent configuration. As a result, both antecedents feature an opposite polarity, summarized by reporting that *Autonomy* displays significance, and *Controllability* is not significant in our study. Further, *Autonomy* moderated by *Gender* has a small but negative effect on *Behavioral Intention,* which complies with the results of Baier et al. (2018). They investigated customers' satisfaction in different conversational commerce use-cases, where four use-cases were referred to as "customer passive," e.g., wherein customers autonomously received information, offers, or recommendations. Customers classified these use cases as "reverse," which means not preferred by customers. These findings can be traced back to the novelty and lack of experience among the participants. Customers who are already more familiar with the technology evaluated the use-cases differently and with much greater enthusiasm (Baier et al. 2018).

In addition to theoretical implications, our study has managerial implications. First, existing smart or digital service can be further developed into PASS, as there are relationships between these types of services (Rau et al. 2020). Second, our results can support the design of PASS and their engagement by revealing which antecedents are valued by customers. At present, *Social Influence* and *Performance Expectancy*, followed by *Adaptability*, are the three main antecedents of PASS acceptance. Therefore, service providers should leverage multiple communication channels and establish customer communities regarding PASS offerings. Given the impact of *Performance Expectancy*, service providers must ensure that service use entails benefits for customers regarding productivity, performance, effectiveness, and reliability. As for *Adaptability*, service providers should integrate different data types, expand partnerships with content providers to improve tailored suggestions, predictions, and decisions provided by PASS, and pay attention to access management and convenient configurability. Third, PASS remains an innovative and emerging topic. Service providers might exploit PASS' full potential by better understanding and influencing customers' processes, gaining new customers, or strengthening existing customer relationships. Early involvement in PASS offers service providers the opportunity to benefit from the insights of early adopters.

6 Limitations and Future Research

One potential limitation of the current study is sample: First, we gathered data from U.S. samples. Hence, our results may differ in other countries due to different economic and cultural contexts. Future research should use data from other countries to challenge the generalizability of our findings.

Second, we only considered customers *'Behavioral Intention to Use PASS'* as dependent variable but did not measure *'Actual Use of PASS'*. Two aspects influenced this decision: 1) PASS are an emerging concept. The literature and practical examples indicate that the diffusion of PASS has just begun. This early lifecycle stage is reflected in the fact that we limited the inclusion in the focus group to academics. Additionally, some antecedents typically included in technology acceptance models were found not to contribute to customers' intention to use PASS in this early development stage. Thus, our insights into customers' intentions to use PASS are valid for PASS' current life cycle and need to be updated in the future. 2) In the empirical part, we use data from a single cross-sectional survey. This leads to conventional limitations in testing actual use: prior research on technology acceptance models and particularly UTAUT propose that researchers must not examine the behavior-intention linkage with cross-sectional data. All responses for all variables have been collected at once. If so, the linkage would be highly inflated (Venkatesh et al. 2003, 2012). Instead, scholars used longitudinal data and conducted two-stage online surveys to collect data on actual use months after training-periods (Venkatesh et al. 2012, 2003). Future research should follow up with generating further empirical insights to test actual use with longitudinal data sets and two-stage surveys after getting used to PASS.

Third, our model does not account for emotional antecedents, which are particularly important for technology acceptance in a 'post-adoptive' stage as the passage of chronological time (i.e., experience) may result in the formation of differing levels of habit or deeply rooted emotion, depending on the extent of interaction and familiarity that is developed with a target technology (Ortiz de Guinea and Markus 2009). Besides measuring actual use of services like PASS, future research should investigate emotional antecedents explaining PASS adoption, such as *Habit*.

Fourth, we primarily focused on PASS' functional and technical properties when deriving our contextualized model's antecedents. Future research may investigate further antecedents, such as to what extent human personality influences PASS use.

Fifth, we did not differentiate the results produced by diverse forms of PASS. However, we used the key forms along a PASS configuration continuum (customer-dependent and autonomous) as examples for the focus group and surveys. Future research may differentiate and compare the results of diverse PASS forms to provide more detailed insights.

7 Appendix

7.1 Appendix A. Introduction to the Survey

With your aid, we want to classify the antecedents influencing the acceptance of Proactive Smart Services. This survey should take on average 8–15 min to complete. Be assured that all answers you provide will be kept in the strictest confidence and only used for scientific purposes. You do not need any previous knowledge to answer the questions—just your opinion is important. The survey contains project-unrelated questions to figure out if the participants have conscientiously answered the questions.

7.1.1 Description of Proactive Smart Services

Proactive Smart Services can be defined as smart services providing high degrees of individualization through learning and a broad source and combination of data, interaction possibilities, and proactivity. Thanks to their tight integration into customers' lives (e.g., knowing customer's preferences, goals, and activities) and their extended capabilities in the analysis of heterogeneous data sources, Proactive Smart Services anticipate customers' needs and provide decision support, assist in the execution of a decision, or even decide on behalf of the customer (e.g., suggestions, predictions, decisions). In doing so, Proactive Smart Services do no longer require customers to make the first move, but instead proactively participate in customers' lives. However, the customer is in control as the services have to be configured (e.g., service's scope of action or degree of autonomy) in advance.

7.1.2 Examples

- "**connected fridge**": Such a fridge orders products autonomously when the supply is about to run out. It buys groceries following customers' preferences and adjusts the quantity with the customers' eating habits and products' expiry date. The purchase is then directly delivered to the customers' home, notifying them with a single message on their smartphones. Customers may thus save time and benefit from the added convenience. They may also benefit economically, as Proactive Smart Service can autonomously select cheaper products.
- "**referencing system**": Such a referencing system suggests newly products in the personal care field which are like prior orders and are in line with customers' preferences. With this, the service sends a single message on customers' smartphones to notify customers of new products. This is done proactively, i.e., with no trigger from the customer. Customers then decide whether to buy the new products. If they decide to buy the product, the service will handle the whole transaction until it is directly delivered to the customer's home. If the customer decides not to buy, the service will ask for feedback to make better suggestions in the future.

7.2 Appendix B. Items of the Contextualized Antecedents

Table 7 Items of the contextualized antecedents

Antecedent	Item ID	Items	Source
Adaptability[a]	IND_01	To me, it is highly important that proactive smart services continuously learn my personal behavior and preferences	Developed following: Lee et al. (2012); Hammer et al. (2015); Wang et al. (2017)
	IND_02	To me, it is highly important that proactive smart services come up with tailored suggestions, predictions, and decisions	
	IND_03	To me, it is highly important that proactive smart services predict my future behavior	
	INT_01	To me, it is highly important that proactive smart services instantaneously act upon my requests	
	INT_02	I expect proactive smart services to provide transparency regarding the offered suggestions, predictions, and decisions	
	INT_03	To me, it is highly important that proactive smart services account for my feedback on suggestions, predictions, and decisions	
	CA_01	To me, it is highly important that proactive smart services consider contextual information	
	CA_02	To me, it is highly important that proactive smart services consider what is going on in my daily life	
	CA_03	To me, it is highly important to give proactive smart services access to other services that I use in my personal context	
	CA_04	To me, it is highly important that proactive smart services also consider relevant publicly available data	

Table 7 (Continued)

Antecedent	Item ID	Items	Source
Trust[a]	TS_01	I would empower proactive smart services to act on my behalf	Developed following: Cabinakova et al. (2016); Leyer et al. (2017); Singh und Matsui (2017)
	TS_02	I would act according to the suggestions and predictions provided by proactive smart services	
	TS_03	I would disclose personal data to proactive smart services	
	TP_01	To me, it is highly important to trust the providers of proactive smart services with respect to what they do with my data	
	TP_02	To me, it is highly important that the providers of proactive smart services are trustworthy companies	
	TP_03	To me, it is highly important to trust that the providers of proactive smart services will protect personal data against stealing and unauthorized access	
	TP_04	To me, it is highly important to trust that the providers of proactive smart services will ensure the appropriate use of my personal data	
Autonomy[a]	AU_01	To me, it is highly important that proactive smart services act without human intervention	Developed following: Leyer et al. (2017); Yang et al. (2017)
	AU_02	To me, it is highly important that proactive smart services act without being triggered	
	AU_03	To me, it is highly important that proactive smart services allow me to make the final decision	
	AU_04	To me, it is highly important to control each activity of proactive smart services fully	
Reversibility[a]	RE_01	To me, it is highly important that I decide in case of once-in-a-lifetime choices	Developed following: Davis et al. (1995); Heal (1977); Moorthy und Srinivasan (1995)
	RE_02	To me, it is highly important that decisions or misinterpreted suggestions are easily reversible	

Please refer to Venkatesh et al. (2012) for the UTAUT2 items

IND Individualization, *INT* Interaction, *CA* Context Awareness, *TS* Trust in Service, *TP* Trust in Service Provider, *AU* Autonomy, *RE* Reversibility

[a]Items are newly developed by following guidelines from Hinkin (1998); Tourangeau et al. (2000); MacKenzie et al. (2011)

7.3 Appendix C. Further Evaluations for the Model Validation

Table 8 VIF of UTAUT2-PASS antecedents

UTAUT2-PASS Antecedents	VIF
Adaptability	2.228
Age	1.115
Autonomy	1.583
Controllability	1.530
Effort Expectancy	2.200
Gender	1.097
Hedonic Motivation	1.550
Performance Expectancy	2.364
Price Value	1.667
Social Influence	2.014
Trust	1.745

Table 9 Effect size of UTAUT2-PASS antecedents

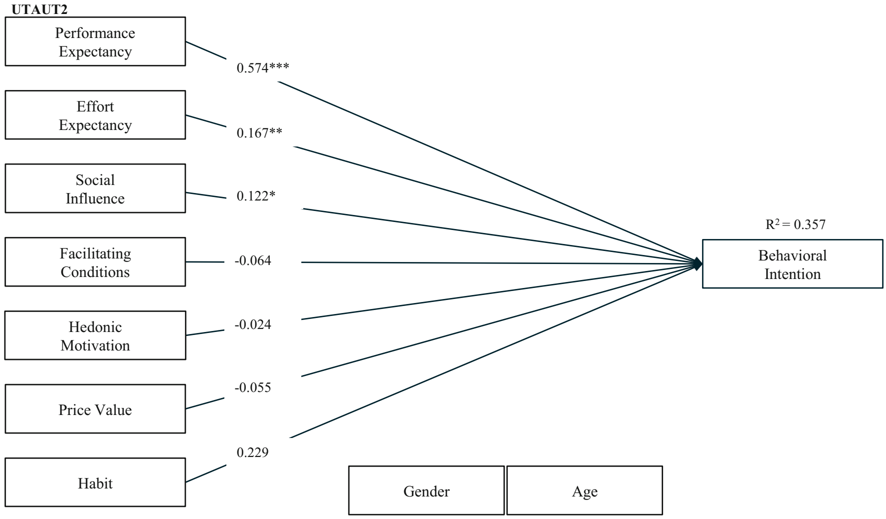
UTAUT2-PASS Antecedents	Effect Size
Adaptability	0.143
Autonomy	0.123
Controllability	0.012
Effort Expectancy	0.106
Hedonic Motivation	0.112
Performance Expectancy	0.288
Price Value	0.004
Social Influence	0.305
Trust	0.003

Table 10 HTMT values of UTAUT2-PASS antecedents

HTMT Values	AD	Age	AU	BI	CO	EE	GDR	HM	PE	PV	SI
Age	0.078	–	–	–	–	–	–	–	–	–	–
AU	0.561	0.047	–	–	–	–	–	–	–	–	–
BI	0.643	0.075	0.520	–	–	–	–	–	–	–	–
CO	0.097	0.053	0.154	0.103	–	–	–	–	–	–	–
EE	0.483	0.028	0.265	0.376	0.311	–	–	–	–	–	–
GDR	0.067	0.051	0.168	0.133	0.065	0.049	–	–	–	–	–
HM	0.419	0.046	0.275	0.470	0.059	0.231	0.046	–	–	–	–
PE	0.605	0.105	0.401	0.630	0.173	0.626	0.014	0.423	–	–	–
PV	0.254	0.029	0.152	0.178	0.308	0.570	0.081	0.171	0.438	–	–
SI	0.588	0.114	0.480	0.682	0.164	0.256	0.123	0.512	0.527	0.136	–
TR	0.104	0.048	0.036	0.038	0.601	0.394	0.076	0.054	0.208	0.339	0.088

AD Adaptability, *AU* Autonomy, *BI* Behavioral Intention, *CO* Controllability, *EE* Effort Expectancy, *GDR* Gender, *HM* Hedonic Motivation, *PE* Performance Expectancy, *PV* Price Value, *SI* Social Influence

7.4 Appendix D. Results of UTAUT2 in the PASS Context



<u>Notes</u>:

1. ****p < .01: **p < .05; *p < .1*
2. For the sake of clarity, we omit the insignificant path coefficients of the moderator *Age* and *Gender*

Fig. 4 Results of original UTAUT2 in the PASS context

Table 11 Descriptive statistics of UTAUT2: correlations and AVEs

	Descriptive Statistics			Correlations									
	ICR	MN	SD	PE	EE	SI	FC	HM	PV	HT	BI	Age	GDR
PE	0.933	0.567	0.083	**0.889**	–	–	–	–	–	–	–	–	–
EE	0.943	0.161	0.076	0.533	**0.924**	–	–	–	–	–	–	–	–
SI	0.945	0.127	0.073	0.547	0.365	**0.949**	–	–	–	–	–	–	–
FC	0.879	–0.064	0.078	0.659	0.550	0.483	**0.821**	–	–	–	–	–	–
HM	0.860	–0.096	0.090	0.736	0.443	0.658	0.634	**0.839**	**–**	**–**	**–**	**–**	**–**
PV	0.942	–0.050	0.062	0.471	0.553	0.244	0.540	0.487	**0.946**	–	–	–	–
HT	0.927	–0.034	0.065	0.507	0.355	0.526	0.577	0.653	0.262	**0.934**	–	–	–
BI	0.933	–	–	0.815	0.523	0.571	0.554	0.710	0.391	0.478	**0.968**	–	–
Age	1.000	–0.018	0.043	–0.046	0.005	–0.082	0.081	–0.150	0.070	–0.060	–0.074	**NA**	–
GDR	1.000	0.020	0.043	–0.132	–0.072	–0.128	–0.097	–0.076	–0.0122	–0.091	–0.080	–0.059	**NA**

Diagonal elements represent AVEs and off-diagonal elements correlations

PE Performance Expectancy, *EE* Effort Expectancy, *SI* Social Influence, *PV* Price Value, *HM* Hedonic Motivation, *BI* Behavioral Intention, *GDR* Gender, *ICR* Internal Consistency Reliability, *MN* Mean, *SD* Standard Deviation

Funding Open Access funding enabled and organized by Projekt DEAL.

Conflict of interest V. Graf-Drasch, M. Röglinger, A. Wenninger and S. Hosseini declare that they have no competing interests.

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