PERSONALIZATION IN MARKETING: HOW DO PEOPLE PERCEIVE PERSONALIZATION PRACTICES IN THE BUSINESS WORLD?

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ABSTRACT

With emerging digital technologies, personalization has become a key activity for marketing strategy to gain competitive success in customer relationships. The aim of this study is to develop and empirically assess a general measurement model of perceived personalization. Multiple data gathering processes and rigorous empirical testing procedures are employed to assess and validate the proposed measurement model. The perceived personalization scale developed in the study rests on the focus of *what is personalized* and includes three main categories: (1) individual-level, (2) social-level, and (3) situation-based personalization. A multidimensional measure of personalization is developed based on these categories and is validated via several tests, including a test of nomological validity exploring the effects of perceived personalization on critical customer responses such as positive emotions, negative emotions, perceived sincerity, satisfaction, and behavioral intentions. These findings shed light on and open new avenues of development for this growing practice for both researchers and practitioners in marketing.

Keywords: Personalization; Individual-level personalization; Social-level personalization; Situation-based personalization

1. Introduction

Marketing efforts providing personalized value offerings to customers involve both individually customized product/service contents and relationship development practices based on personalized characteristics of individual customers (Rust, 2020). These efforts have become a critical driver of competitive success in today's data-based decision making and knowledge-driven business environment (Strycharz et al., 2019; De Keyzer et al., 2022; Singaraju et al., 2023). The ongoing and expected developments in information technology and artificial intelligence seem to have accelerated the rise of personalization practices as a core component of business models in virtually all industries since these technologies have started to be included and used in the development process of personalized value offerings to customers (Yang & Padmanabhan, 2005; Salonen & Karjaluoto, 2016). Most prominent examples of such

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personalization practices today include Youtube’s individualized video content display and Netflix’s personalized suggestions (Kannan & Li, 2017).

Personalization in marketing involves effective use of individual-level information in all forms of interactions and transactions with customers (De Keyzer et al., 2022; Ho et al., 2007; Kwon & Kim, 2012; Ng & Wakenshaw, 2017; Singaraju et al., 2023; Tam & Ho, 2006;) and plays a vital role in customer decision-making (e.g., Xu et al., 2011), persuasion (e.g., Tam & Ho, 2005), evaluation and loyalty development processes (e.g., Pappas, 2018). While the practice of personalization may have existed since the very beginning of exchange, it is not only limited to digital contexts and not a newly discovered concept. There is no doubt that the recently emerging technologies have enabled enriched and immensely more effective uses of personalization. Thus, given the rapidly increasing importance of this phenomenon in marketing practice, extant research about personalization needs further development in a variety of crucial areas. One of these areas is consumer behavior research examining customer evaluations about these personalized value offerings. Understanding how consumers perceive such personalization practices has a vital role here for further development of the area in this manner. It is important to note at this point that actual personalization (i.e., personalization practices designed and implemented by business firms) and customer perceptions about personalization may not always refer to the same set of practices (Li, 2016), and since customer responses would be the key issue in personalization, the conceptualization and operationalization of the concept should mainly focus on how personalization practices are perceived by their targets.

Current conceptualizations and operationalizations of the personalization construct seem to fail to cover the prominent aspects of the domain definition of this rather broad, complicated, and rapidly evolving practice, and to reflect customer perceptions towards these practices that have such features. Indeed, since its early conceptualizations, personalization has been viewed as a multidimensional construct. Surprenant and Solomon (1987), for example, emphasized that the personalization construct in a service setting is multidimensional and has three dimensions (i.e., option personalization, programmed personalization, customized personalization). It has been highlighted in ongoing conceptualization efforts that there are both different types of personalization and different types of variables in the personalization process (Vesanen, 2007), and thus personalization is still referred to as a multidimensional construct. Similarly, it is reported in many studies that there are different types/categories/classifications of personalization (e.g., Kwon & Kim, 2012; Kingsnorth, 2019). However, when we consider the issue from the consumer’s perspective and concentrate on how personalization is perceived, we can find one-dimensional personalization measurements (e.g., Alimamy & Gnoth, 2022; Ball et al., 2006) but cannot see the multidimensional operationalization of that multidimensional construct.

Moreover, there are some future research calls that make it necessary to understand how personalization is interpreted by consumers and to do this in a multidimensional way. Riegger et al. (2021), for example, focused on technology-enabled personalization and emphasized the importance of researching the impact of personalization on consumer perception. This study provides an answer to this call, with a focus on perceived personalization. Lambillotte and Poncin (2022), on the other hand, emphasized that in one call, the individuals and their characteristics should be prioritized, and that in another call, a scale should be developed to address different types of personalized content. Although we did not use the classification of that study directly, we did respond to this call by developing a multidimensional scale that addresses different dimensions of personalization, as stated. The need for developing a comprehensive multidimensional measure of personalization practices stems from the fact that if we fail to develop a broader perspective to understand the real nature of this complicated and dynamic construct, many progresses in the practice of marketing that are likely to emerge due to technological advances might go overlooked by the academia. Similarly, from the practitioners’ viewpoint, since the perception of customers regarding these practices would likely have impacts on a multitude of critical customer responses, and since such effects could also vary across customer segments and product categories, insights regarding the nature of such uncertain outcomes would undoubtedly prove valuable. Thus, a comprehensive approach to conceptualizing and operationalizing the perceived personalization construct that captures the wide variety of different current practices in business world as well as possible progresses likely to emerge via forthcoming technological developments is necessary. A perceived personalization insight that is capable of capturing differentiating personalization practices and enabling a multidimensional approach to studying this phenomenon, particularly in terms of exploring the antecedents and outcomes of personalization in different business contexts, would constitute a fruitful pathway to expand the current state of knowledge in this area. The present study aims to address both issues.

Specifically, this study (1) based largely on the framework introduced in Cavdar Aksoy et al. (2021), develops a general and multidimensional measure of perceived personalization that is applicable in all business settings, (2) improves the scale development studies and personalization studies in the literature with rigorous empirical testing, including individual-level, social-level, and situation-based personalization sub-dimensions, (3) also enhances the literature by detailing the sub-dimensions where individual-level and situation-based personalization occur, respectively, as *past digital behavior and attitudes & preferences*, and *time-based, and location-based*, (4) explores the key outcomes of perceived personalization in different empirical settings and statistically proves that this multidimensional personalization affects positive emotions, negative emotions, perceived sincerity, satisfaction, and behavioral intentions, and (5) with all these features, provides a comprehensive personalization conceptualization and operationalization that reflects today's up-to-date personalization approach. Through these contributions it is expected that marketers would understand, study, and manage personalization processes more effectively and predict future developments in this practice more confidently since (i) they can find the way of an effective starting point for the development of a personalization practice by observing the answer of the question 'what is personalized', and more importantly, (ii) they can gain customer insight and see customer responses starting from understanding customer perception about the related personalization practice. Conceptualization and operationalization of perceived personalization in our study also provide an effective tool for academia (i) to capture the technological advancements in the practice of personalization in marketing through prominent aspects of it in order to measure and evaluate a personalization strategy including various dimensions in a customer-centric way, and (ii) to analyse further customer evaluations and responses towards these practices by gained multidimensional measurement tool which represents practices in this field holistically.

2. Literature Review and Conceptualization

Since personalization is a concept that has been studied in various disciplines for years, it is defined and explained in several distinctive ways (Fan & Poole, 2006) and the operationalization of it is also highly variable (Wang et al., 2017). Personalization, on the one hand, is defined as a strategic tool used for differentiation in competitive environments (Ho, 2006; Kwon & Kim, 2012; Tam & Ho, 2006) and represents providing "the right content in the right format to the right person at the right time" (Tam & Ho, 2006, p. 867). Since we focus on reflections of personalization on marketing practice, the consumer-related definitions were examined and seen that the phenomenon is defined as a customer-oriented, relationship building-centered marketing strategy including recognizing and treating customers as individuals that have unique needs, characteristics, behaviors, etc. through personal value offerings (Imhoff et al., 2001; Tam & Ho, 2006; Aguirre et al., 2015; Nyheim et al., 2015; Kotras, 2020). From this perspective, we define personalization as an essential activity of the marketing strategy that plays a vital role in today's data-driven business world and that aims to provide value based on personal information obtained from the first contact with customers.

Today, companies offer a wide variety of personalized consumption experiences that bring benefits both for customers (finding the best fit) (Ho & Lim, 2018) and companies (increased customer loyalty) (Kramer et al., 2007). Such personalization practices *basically "individualize" and "situationalize" some or all elements of the marketing mix* (Montgomery & Smith, 2009; Tam & Ho, 2006). Some scholars have noted that the personalization phenomenon is particularly relevant to consumption contexts involving electronic consumer experiences (McCarthy, 2001). Included among such contexts are e-commerce personalization (e.g., Adolphs & Winkelmann, 2010), website personalization (e.g., Oberoi et al., 2017), and technology-mediated personalization or technology-enabled personalization (e.g., Shen & Ball, 2009; Riegger et al., 2021). E-commerce personalization refers to selecting content specifically based on customer properties to increase business outcomes for an e-commerce platform. Website personalization is an automated process that identifies individuals by monitoring their movements, creating a pattern by analysing the movements of similar users, thus presenting tailored and individualized product-, communication-, and pricing-related contents matching their preferences. Technology-mediated/technology-enabled personalization derives from creating personalized interactions and services based on customer databases and applications software. The emergence of recent cognitive technologies (e.g., big data analyses, machine learning, artificial intelligence, etc.) has further boosted the personalization phenomenon to even much prominent levels and to virtually every business context (Huang & Rust, 2017).

To understand personalization phenomenon with its unique sides and to clearly conceptualize and operationalize the perception of customers toward it, the differences between personalization and related practices, such as customization, should be underlined first. Personalization is a company-initiated practice (i.e., the company finds and offers the best option to the individual using customer data), whereas customization is a customer-initiated concept (i.e., the customers are empowered to have a unique experience by making their own choices) (Arora et al., 2008; Montgomery & Smith, 2009). Besides, personalization is generally used as a broader, umbrella term, and customization is seen as one amongst many methods of implementing it (Fan & Poole, 2006). Similarly, recommendation agents and recommendation systems are basically specific applications of personalization via different technological platforms and should not be seen as reflecting all forms of personalization (Komiak & Benbasat, 2006; Zhang & Curley, 2018). Recommendation systems are web-based technologies that collect information about customer preferences to present the most suitable products or services to the individual (Li & Karahanna, 2015).

Likewise, recommendation agents are software agents used for advising individuals during decision making stages and showing them what to buy in line with their needs and preferences (Wang & Benbasat, 2005). Personalization should also not be confused with perceived interactivity, which refers to a much broader set of customer interactions particularly in service settings (Alalwan et al., 2020).

2.1. Existing Personalization Scales

Extant research on personalization mostly focused on a single business context and measured personalization practices specifically within these contexts. Examples include studies focusing on personalization in fashion mobile applications (e.g., Trivedi & Trivedi, 2018), banking (e.g., Ball et al., 2006), advertising (e.g., Ham, 2016), social media and social network sites (e.g., De Keyzer et al., 2015), online brand communities (e.g., Kang et al., 2016), healthcare services (e.g., Liu & Tao, 2022), online shopping (e.g., Alimamy & Gnoth, 2022). In the works exploring personalized advertising, for instance, perceived personalization is operationalized as an ad characteristic or a component of the ad itself (Bleier & Eisenbeiss, 2015; Boerman et al., 2017; Tran, 2017; Tran et al., 2021). While all these studies have contributed significantly to our understanding of the personalization phenomenon, the approach in the present study is different in the sense that developing a general measurement approach to perceived personalization that could be adapted to all business settings. The perceived personalization scale in this study did not only focus on a specific context like advertising, e-commerce, etc. and therefore, it is adaptable for various business context.

Recent cognitive technologies get involved in the development processes of personalization practices and become an inseparable part of some business models. When we examine personalization strategies in such business models, we can observe several different personalization approaches provided to customers to create value for them. Besides, personalization is seen as a prominent factor in evaluating customer perceptions toward emerging technologies, such as smart devices (Henkens et al., 2021). Existing personalization scales, however, mostly focus on the customers' evaluation in an unelaborated way based on the approaches the strategy involves. We cannot see the perception of customers about different personalization dynamics and approaches applied for creating personalized value offerings based on the personalization strategy. For instance, Netflix uses various methods in creating personalized value offerings for customers and also in providing them into customers (i.e., based on content categories, based on past watched contents, based on used visualizations in posters etc.). Existing scales fail to cover the prominent aspects of these practices and thus, fail to understand how customers perceive such broad personalized offerings which actually consist of all these methods and approaches to create and provide personalized value.

Since the personalization practices have a broad perspective including several different personalized value offerings to customers, conceptualizing and measuring perception toward these practices would require the exploration of a workable classification to capture the dimensions in these practices which are also potential dimensions of that measurement tool and show us the phenomenon's multidimensional nature. We discuss the personalization classifications in extant literature next that we adopted them to use as dimensions of this construct in this study.

2.2. Dimensions of Personalization: Revealing Different Personalization Approaches

Since prior research seems to have approached the personalization phenomenon in a more specific manner and focused mainly on a single application context of personalization, one difficulty in categorizing different personalization practices arises from the fact that specific personalization types identified so far appear to reveal some but not all context-independent dimensions of this practice (Kwon & Kim, 2012).

When the extant literature on personalization is examined, various focuses emerge by several different studies. Surprenant and Solomon (1987), in what was possibly one of the first conceptualizations of personalization, argued that personalization has three dimensions. *Option personalization* involves providing the customer with a menu of alternatives from which they can select the best one for their specific needs. It is critical in *programmed personalization* to make the customer feel special when interacting with them: calling them by name, making small talk, and so on. *Customized personalization*, on the other hand, requires individual attention by assisting the customer, and support is provided in the most appropriate manner. Vesanen and Raulas (2006) explained that there are two variables in the personalization process: objects and operations. Operations describe what happens at various stages of the process, whereas objects describe the items required to carry out the operations. Fan and Poole (2006) argued that personalization studies can be grouped into three main approaches: what is personalized (functionality, content, interface, channel), for whom it is personalized (individual or group), and who does the personalization. Koch and Benlian (2015) suggested that there are three aspects to personalization studies. One of them is concerned with personalization application methodologies, specifically how to collect data from individuals. Another type of study is one that focuses on the value that personalization brings to the customer or the company. The final one focuses on the boundary conditions of personalization, including obtaining different benefits and the comparison of them. Taking personalization with a focus on email marketing, Sahni et al. (2021) moved forward with a more specific area as an example and presented three main personalization approaches: personalization for attention, personalization that serves as a positive cue and drives behavior, and personalization that increases communication elaboration. Song et al. (2021) clarified that personalization studies have two aspects. One is concerned with the end result of personalization, while the other is concerned with the automated tailoring process (who collects information, what information is collected, how information is collected and analyzed, etc.). Based on Cavdar Aksoy et al. (2021), the personalization phenomenon could be explicated and categorized on the bases of several different focuses: what is personalized, how the personalized design is communicated to the customer, who does the personalization, what kinds of data are used, where the data comes from, and how it is personalized. Among these, the focus of “what is personalized”, i.e., *what aspects of the individual is utilized for personalization* draws attention based on our approach in this study. It can be exemplified with some prominent personalization categories, such as link personalization, content personalization, context personalization, functionality-based personalization, transaction-driven personalization, content-based personalization, collaborative personalization, social network-based personalization, location personalization, information personalization, perceived personalization, individual-level personalization, social personalization, time personalization, and real-time personalization. Some other focuses, which were used to present personalization categories are somehow deriving from the finding the way of creating or presenting personalization practices based on utilized technologies (i.e., authorized personalization, humanized personalization, channel/information access-based personalization, context-driven personalization, behavioral personalization, interaction process-based personalization), the control mechanism in it (i.e., control personalization, customized screen design personalization, user-driven personalization, proactive personalization, reactive personalization, actual personalization), data gathering processes to develop them (i.e., implicit personalization, explicit personalization, overt personalization, covert personalization, user-initiated personalization, system-initiated personalization, user-defined personalization), the presentation methods to provide them to customers (i.e., anthropomorphic personalization, user interface-based personalization, adaptive personalization, static personalization, presentation personalization, navigation personalization), are including rather technical issues.

Obviously, every single one of the aforementioned personalization focuses and gathered categories are important and may lead to meaningful classifications of the personalization phenomenon in revealing personalization dimensions to understand how it is perceived. However, the focus of *what is personalized* (Fan & Poole, 2006; Cavdar Aksoy et al., 2021) and revealed sub-categories (Cavdar Aksoy et al., 2021), appears to be by far the most relevant issue to even begin understanding the nature of and predict the future developments in this rapidly changing technique and explaining the phenomenon through the eyes of customers. On the one hand, rapidly developing information technologies are offering new avenues for marketers to practice novel personalization approaches and every single technical focus in personalization listed above should be expected to change dramatically with the emerging new technologies. The focus of *what is personalized*, that is expected to resist and remain unchanged for a longer time period, particularly in terms of its fundamental structural characteristics (e.g., dimensionalization). The reason for the proposed relatively more resistant nature of this focus to is based on the expectation that technological advances could only shape the depth and the extent of individual characteristics that are to be used in personalization practices, but aspects and specific behaviors of individuals that are likely to be used in personalization practices are less likely to change. Decades of research in marketing has already established the strongest determinants of customer responses in consumption settings. Furthermore, the main structural characteristics of such data, specifically the dimensions of what is to be personalized, is expected to remain even more resistant. In all other focuses, a data-dominated structure is observed, and as the data-based technological developments continue one would expect rapid changes in the ways these criteria are applied for personalization purposes. In addition, from a practical point of view, the question of *what is to be personalized* will always be the first issue to address (since that is what really determines customer responses), and all others will constitute secondary concerns.

On the other hand, using multiple criteria to develop a measurement tool would yield a richer dimensionalization and therefore should be preferred. Nonetheless, it also critically important that, from a methodological perspective, a good taxonomy must generate mutually exclusive categories, and the use of multiple categories from several different focuses impedes this purpose since with multiple focuses overlap amongst categories seem to be unavoidable. The only way to create a mutually exclusive conceptualization for perceived personalization is to proceed with a single focus, and *what is personalized* would be the obvious choice in this case due to its unchangeable nature and its benefits about providing a starting point for practitioners. It is also important to note that personalization practices in marketing is not specific to the digital age; such practices have been used for centuries in different forms (i.e., personalized services, personalized shopping orientation, personalized in-store implementations, personalized coupons, personalized communication with customers (Mägi, 2003; Chellappa & Sin, 2005; Ghosh & Dekhil, 2007), and, in this regard, the first criterion also plays a vital role in terms of reflecting this historical perspective.

2.3. Our Conceptualization: A Multidimensional Personalization Construct

By following Fan and Poole (2006) and Cavdar Aksoy et al. (2021), we specifically propose that, using the *what is personalized* focus finding the answers to such question for various business context through the eyes of customers, personalization practices could most effectively be classified in terms of three main characteristics to use them as personalization dimensions: (1) individual-level personalization, (2) social-level personalization, and (3) situation-based personalization. Individual-level and Situation-based personalization practices are further dimensionalized into sub-categories. Extant research on personalization shows that personalization practices are created in more than one category in general although we sometimes can observe personalization studies which is specific to one single personalization category. There is no doubt on that each personalization category is open to research and further developments in this specific practice. However, we cannot ignore multidimensional nature of this phenomenon so that a personalization strategy mostly includes several different methods to create personalized value offerings in practice which can also be seen in extant research. Because of this, when understanding the perception of customers on this phenomenon, this multidimensional nature of the construct should be taken into consideration. On the other hand, these three levels of information (individual-level, social-level, situation-based) represent prominent personalization types in extant research.

For instance, individual-level personalization approach is very common in extant research but is named in different ways. Kingsnorth (2019), for example, classifies personalization as only two categories and these have the same focus for this reason. In our approach, these two categories are two sub-categories of individual-level personalization based on this prominent approach in the literature. Social-level personalization derives from 'social impact' focus in extant research on consumer behavior and we can also see some examples of it in personalization research (i.e., social network-based personalization). Since we also know that personalized value offerings are not thought without social environment of customers in practice today, it represents a main category in our approach. Concerning the real-time of customers in gathering and using information like in real-time personalization, situation-based personalization is the other category in our approach. Time and location information here serve at the same purpose and represent two complementary concepts to understand individuals' situation that they are in (Dey, 1997; Abowd, 1999) and thus, constitute situation-based personalization categories in our approach. We now discuss each personalization dimension in further detail to provide the rationales for each dimension.

We wanted to move forward with these three categories in particular because we were convinced that they are also included in the literature in a scattered manner, that they are particularly prominent in personalization practices, and that they are types that we believe will guide theoretical progress in understanding reflections of personalization in consumer perception. As previously stated, these information levels are found differently (e.g., different names, categories, classifications, etc.) in several different studies (e.g., Kingsnorth, 2019). Furthermore, it was decided that they should be combined into a unified whole. Individual-level refers to placing the individual in the center with all of his/her characteristics and examining the issue in terms of attitudes, preferences, and behaviors. We believe that this topic deserves to be classified as a separate category. When it comes to the other two categories, it is critical to consider both the individual under consideration and *the surrounding environment*. In these categories, the individual's immediate surroundings begin to play a role. Personalization is carried out in social-level personalization by taking into account the presence of people who have influence in their environment, and the contribution of online social group influence to this situation in the current age we live in. Time and location together represent situational factors, and it is critical to consider the individuals' situations here. In this regard, we incorporated an examination of individual, social, and situational factors from existing marketing and information management disciplines (e.g., Bagozzi, 1986; Neufeld & Fang, 2005), as expanded by Cavdar Aksoy et al. (2021) for personalization conceptualization, into our scale development study specific to the personalization phenomenon.

Detailed information about unique sides of each information level can be seen in Table 1.

Table 1: Characteristics of Personalization Levels

Information Level	Similar Conceptualizations in Extant research	Unique Sides/Contributions
Individual-level	Link personalization, transaction-driven personalization, behavioral personalization, individual-level personalization	It combines personalization approaches that take individual preferences and reactions into account. It addresses a variety of issues at the individual level, which the individual reflects towards environmental stimulus. It considers not only behavior but also preferences and attitudes. This individual-centered approach is inclusive and reliable in terms of displaying consumer responses obtained from the individual.
Social-level	Social network-based personalization, traditional peer-based personalization, adaptive, personalization, social personalization	It considers the individual's surrounding environment. In doing so, it takes into account not only the offline social groups but also the effects of the connections in the online world. In this respect, it is inclusive one and offers a reflection of an integrative social environment.
Situation-based	Real-time personalization, time personalization, location personalization, location-aware personalization	It takes into account the individual's immediate surroundings and therefore, current situation. It is all-inclusive in that it provides two foci. It illuminates the situational factors by communicating the evaluation of the individual's time and location information.

Note: Closely related concepts were not included in this examination.

2.3.1. Individual-level Personalization

Information generated from individuals' past digital behaviors and/or attitudes and preferences, online or offline, constitutes individual-level personalization practices. The first type of personalization at the individual level is past digital behavior. This personalization refers to collecting information about an individual by taking into account how the individual has been acting digitally in the past (past search behavior, purchasing behavior, digital experiences, etc.) and making personalizations for him/her in the light of this information. Relevant *digital behaviors* include individual-level data about purchases, reviews, sites visited, social media posts, likes, comments, etc. (i.e., link personalization, transaction-driven personalization, implicit personalization, content-based personalization, collaborative personalization, system-initiated personalization, information personalization, behavioral personalization, proactive personalization). In the world of data and analytics, Geodata (geographic information derived from digital services such as Google Maps) reflects such sort of personalization (Abernathy, 2016), including check-in data, restaurant reviews, and routes/directions explored. Netflix also uses such personalization approaches by providing recommendations to clients based on their past choices. Likewise, most e-commerce sites promote products from the ads one has previously viewed and examined on the web to the same individual. Such practices have been developing together with digital technologies day by day.

The second type of personalization at the individual level uses individuals' revealed attitudes and preferences. This personalization means collecting information about the individual by taking into account the current digital behaviors or general preferences and attitudes in his/her life and making personalizations for him in the light of this information. *Attitudes & preferences* focuses on direct attitudinal measurements obtained from individuals via marketing research applications or inferences obtained through preferences of individuals regarding attitudinal standing, using such techniques as users' clickstreams, actions in a session (Ho et al., 2007), and digital movements (Moe & Fader, 2004) (i.e., control personalization, customized screen design personalization, context personalization, user-driven personalization, explicit personalization, user-initiated personalization, user-defined personalization, content-based personalization, information personalization, reactive personalization). Tracking and observing the movements of the person or trying to recognize him/her by directly requesting information could also be the basis of data used for this form of personalization. Since both behaviors and attitudes are individual-level characteristics, these two dimensions are posited as specific components of individual-level personalization.

2.3.2. Social-level Personalization

Most prominent form of social-level personalization involves personalized recommendations offered to individuals addressing the choices of significant social circles (Arazy et al., 2010). Personalization at the social level refers to collecting information about an individual by taking into consideration the individual's social environment and his/her evaluations about this environment and making personalizations for him/her in the light of this information (i.e., social network-based personalization). In many e-commerce platforms, for instance, some social groups are created considering the importance of social influence in consumer behavior and it was assumed that these groups of individuals have similar likes, preferences, and shopping behaviors so that they are recommended similar products (Li & Karahanna, 2012; Schroeder, 2014; Zhao, 2013). This data becomes a source for deciphering similar preferences of 'similar users' to create comparable customer groups (Ochi et al., 2010). Social networking platforms have naturally also become the most effective platforms for the implementation of this type of personalization (Chung et al., 2016; Li and Karahanna, 2012) and there, similar users also explored including both close friends, family members, peers of individuals and others that the user does not actually know. Instagram's 'explore' feature can exemplifies such social network-based personalization approach, which portrays user likes, comments, connections and then, show personalized contents based on the users' social circles on that platform to create personalized value offerings for them. In Facebook's friend suggestions, we can see 'you may know' or product recommendations as an example of such sort of personalization since these recommendations recognize the social circle of the users and then create personalized suggestions for them.

2.3.3. Situation-based Personalization

This form of personalization relies on information about the specific locations of individuals, the characteristics of the situation being experienced, and/or the time frame the individual is currently experiencing. Both location and time convey rich ingredients in terms of shaping the impacts of surrounding elements on personalized experiences (Choi et al., 2017; Fan & Poole, 2006; Schilke et al., 2004; Wang et al., 2010). Time personalization refers to collecting information about an individual by taking into account what the individual is doing at current time and making personalizations for him/her in the light of this information (i.e., real-time personalization). Location personalization refers to collecting information about the individual regarding his/her current position and where he/she is located and making personalizations for him/her in the light of this information about the nature of the experiences the person is having (i.e., location personalization, navigation personalization). Location aware mobile coupons that inform services based on locations of individuals (Xu et al., 2011) are examples of location-based personalization practices (Germanakos et al., 2005); Ho & Chau, 2013. Region-specific applications have been carried out even by regional administrations for years, and, with the rise of digital technologies, these applications have become more advanced, particularly via mobile phone signals and location services. Event suggestions made based on certain routines or calendars of individuals (Schilke et al., 2004), e-mails reminding past locations of individuals (i.e., 'Last year today you were in the city of Rome' by rentalcars.com) are the examples of time-wise information in personalization practices. Biletix, an online event ticket sales platform in Turkey, creates personalized offerings that combine these two methods. For example, Biletix makes notifications for their users and reminds them events that may prefer, 'This concert comes to your city.', 'It is your favorite time to go to a concert.'. Digital services such as Netflix and Google also analyse consumers' consumption patterns, locations, calendars, and provide personalized recommendations for them.

All these examples show us the prominent personalization categories, which can be achieved through an in-depth examination of personalization classes / types and the focuses in providing these categories. These examples and explanations show us the features of the related category based on extant research on personalization. Considering this information, we named and integrated them first and then, held them as personalization dimensions in our study since they are strong together to reflect a personalization strategy in terms of personalized value offerings to customers. The following sections of this paper focus on developing a measurement scale that captures these three major forms personalization.

3. Scale Development

The measure development process followed in the present study is based on established scale development procedures (Churchill, 1979; DeVellis, 2003; Gerbing & Anderson, 1988) and involves the six steps illustrated in Figure 1. We now explain each step in further detail.

1) Item generation and selection	Literature review
5 dimensions, 46 items	4 marketing scholars, 15 PhD students, 30 consumers
2) Initial purification and content validity	Evaluation phase by scholars
5 dimensions, 33 items	5 researchers of marketing and 3 researchers of technology management
3) Initial purification and face validity	Evaluation phase by marketing practitioners
5 dimensions, 24 items	2 brand managers, 4 digital marketing managers, 2 company managers, 2 digital agency owners
4) Item reduction and initial scale dimensionality	Item refinement and scale dimensionality
5 dimensions, 19 items	Survey with 320 consumers
5) Confirmation of the dimensions	Scale validation
5 dimensions, 19 items	Survey with 277 consumers
6) Exploring the outcomes of personalization	Using personalization to predict consumer behavior
5 dimensions, 19 items	Survey with 430 consumers

Figure 1: Development Process of The Multidimensional Personalization Scale

3.1. Study 1: Generation of the Item Pool

Study 1 aims to generate a broad list of items capturing specific components of the domain definition and dimensions of personalization. As mentioned before, we first conducted an extensive literature search within platforms such as Web of Science, Scopus, Google Scholar to see personalization categories and focuses in extant research on personalization to utilize them as the dimensions this phenomenon. Here, we included published works (journal articles, conference proceedings, books, and book chapters) that (1) have a business perspective in general, (2) view and study personalization as a global construct, (3) focus on only one or more sub-dimensions of personalization, e.g., personalization using recommendation agents or location-based personalization, or (4) focus on concepts closely related to personalization, such as customization, bespoke, tailor-made. The list of specific keywords used during this literature search include personalization, perceived personalization, customization, personalized offerings, personalized experience, personalization practices, bespoke, and tailor-made. We are re-exploring closely related concepts in order to see if the focus of personalization is included in some studies on these concepts. In some customization studies, for example, the application in question is seen as company-initiated rather than individual-initiated, and personalization scales are used as a scale in those studies. This research is also included in our generating scale pool study, which can be found here. Besides, we also searched each personalization category that should be reexamined within the focus of *what is personalized* (e.g., link personalization, location personalization, etc.). Then, we gained several different personalization categories which have various focuses to study personalization. As noted before, on the basis of the focus "what is personalized" (e.g., Cavdar Aksoy et al., 2021; Fan & Poole, 2006), the hierarchical classification that first categorizes personalization practices into three first-order dimensions (individual-level personalization, social-level personalization, and situation-based personalization) and then further divides individual-level personalization into two sub-dimensions (past digital behavior and attitudes & preferences) and situation-based personalization into another pair of sub-dimensions (time-based and location-based) was then developed. This classification system categorizes all specific approaches to, and dimensions of personalization identified in prior research into one of the dimensions or sub-dimensions in a mutually exclusive manner. Besides, we also searched for existing scales in extant research on personalization. Here, we examined the studies for personalization categories again whether they include a personalization scale and also conducted an additional search for such scale. In this phase, we examined all personalization research articles which used personalization as a dimension in their research models. Then, we gained the scales named personalization, customization, perceived personalization, personalized services, and web personalization. These scales were used in research articles which examine the effective factors on personalization or the effect of personalization on some outcomes or some relationships. Since we did not especially search for other dimension names such as customization here, we observed that some personalization research was conducted through such dimensions to understand the existence of personalization. The full list of prior works utilized during this item generation process is provided in Table 2.

Table 2: The Full List of Papers Used to Prepare the First Set of Items

The Name of the Scale	Study	Context	Items
Personalization	Lavado-Nalvaiz et al., 2022	Smart home speaker	The information provided by my smart home speaker is tailored to me. The content of the information provided by my smart home speaker is personalized. The information provided by my smart home speaker is personalized for my usage. The information provided by my smart home speaker is delivered in a timely way.
	Su et al., 2022	Mobile food delivery apps	I can save my order details for my future orders The MFDA stores my food preferences or habits and offers me suitable products/services The MFDA predicts what kinds of products/ services I might want and make suggestions The MFDA has features that are personalized for me The MFDA presents logical filter functions (e.g., coupons, discounts, customer feedback, etc) to search for my specific needs The MFDA provides helpful options to search for my specific needs
	Alimamy and Gnoth, 2022	Online shopping	IKEA offers me products and services that satisfy my specific needs IKEA offers products and services that I couldn’t find with another retailer If I changed retailers, I would not obtain products and services as personalized as I have now IKEA understands my needs IKEA knows what I want IKEA takes my needs as its own preferences

	Liu and Tao, 2022	Healthcare services	mart healthcare services provide personalized services that are based on my information Smart healthcare services personalize my health management experience Smart healthcare services personalize my health management by acquiring my personal preferences Smart healthcare services personalize and deliver healthcare services to me according to my information Smart healthcare services deliver personalized healthcare services
	Alalwan et al., 2020	Mobile shopping	Mobile shopping apps enable me to order products or services that are tailor-made for me The advertisements and promotions that mobile shopping apps send to me are tailored to my situation Mobile shopping apps make me feel that I am a unique customer Personalized offers are given by mobile shopping apps Personalized messages are sent by mobile shopping apps Mobile shopping apps offers customized information search
	Trivedi and Trivedi, 2018	Fashion mobile applications	The services of fashion m-commerce apps are often personalized for me The fashion m-commerce apps treat me as an individual unique customer When communicating with the fashion m-commerce apps I am often addressed using my name
	Ball et al., 2006	Banking	My bank” offers me products and services that satisfy my specific needs “My bank” offers products and services that I could not find in another bank If I changed from banks I wouldn’t obtain products and services as personalized as I have now
	Xu, 2006	Mobile advertising	I feel that mobile advertising displays personalized message to me I feel that mobile advertising is personalized for my usage Contents in mobile advertising are personalized
	Mittal and Lassar, 1996	Services-	Everyone at is polite and courteous The employees display personal warmth in their behavior All the persons working at are friendly and pleasant The employees take the time to know you personally

Customization	Harris and Goode, 2010	Online shopping	This web site is tailored toward me If I wanted to, I could customize this web site to what I like (e.g., changing colors, layout, fonts etc.) I feel that this web site is designed for me The services of this web site are often personalized to me That this web site treats me as an individual When communicating with this web site I am rarely addressed using my correct nameThis web site makes purchase recommendations that match my needs
	Srinivasan et al., 2002	E-commerce	This website makes purchase recommendations that match my needs This website enables me to order products that are tailor-made for me The advertisements and promotions that this website sends to me are tailored to my situation This website makes me feel that I am a unique customer I believe that this website is customized to my needs
Perceived personalization	Tran et al., 2020; Tran, 2017	Advertising	Personalized advertising of this brand on Facebook makes purchase recommendations that match my needs I think that personalized advertising of this brand on Facebook enables me to order products that are tailormade for me Overall, personalized advertising of this brand on Facebook is tailored to my situation Personalized advertising of this brand on Facebook makes me feel that I am a unique customer I believe that personalized advertising of this brand on Facebook is customized to my needs
	Shanahan et al., 2019	Social media	This ad makes purchase recommendations that match my needs I think that this ad enables me to order products that are tailor-made for me Overall, this ad is tailored to my situation This ad makes me feel that I am a unique customer I believe that this ad is customized to my needs
	Zhang and Curley, 2018	Online recommender agents	This RA understands my needs This RA knows what I want The advice appears to tailored for me personally
	Ham, 2017	Online behavioral advertising	Personalized message of OBA makes purchase recommendations that match my needs

			I feel that personalized message of OBA enables me to know products that I'm interested in Overall, personalized message of OBA is tailored to my situation Personalized message of OBA makes me feel that I am a unique customer I feel that personalized message of OBA is customized to my needs
	Guo et al., 2016	Mobile health services	[By disclosing my information], [mobile health service provider] can understand my needs[By disclosing my information], [mobile health service provider] can know what I want [By disclosing my information], [mobile health service provider] will take my needs as its own preferences
	Kang et al., 2016	Online brand community	This online brand community understands my needs This online brand community knows what I want This online brand community takes my needs as its own preferences
	De Keyzer et al., 2015	Social network sites	The information was fully tailored to my personal profile
	Nyheim et al., 2015	Restaurant smartphone advertising	Personalized advertising on this application makes purchasing recommendations that match my needs I think that personalized advertising on this application enables me to order products that are tailor-made for me Overall, personalized advertising on this application is tailored to my situation Personalized advertising on this application makes me feel that I am a unique customer I believe that personalized advertising on this application is customized to my needs
	Baek and Morimoto, 2012	Advertising	This personalized advertising on [MEDIA TYPE] makes purchase recommendations that match my needs I think that this personalized advertising on [MEDIA TYPE] enables me to order products that are tailor-made for me Overall, this personalized advertising on [MEDIA TYPE] is tailored to my situation This personalized advertising on [MEDIA TYPE] makes me feel that I am a unique customer I believe that this personalized advertising on [MEDIA TYPE] is customized to my needs

	Komiak and Benbasat, 2006	Web based product-brokering recommendation agents	A understands my needs, personalization This RA knows what I want This RA takes my needs as its own preferences
	Wu and Wu, 2006	Perceived interactivity of websites	I felt I just had a personal conversation with a sociable, knowledgeable and warm representative from the company The Web site was like talking back to me while 1 clicked through the website I perceived the website to be sensitive to my needs for product information
Personalized service	Dang et al., 2020	Online shopping	The products and services on Taobao are personalized to my needs Taobao makes purchase recommendations that match my needs Taobao enables me to order products that are tailor-made for me The advertisements and promotions that Taobao sends to me are tailored to my situation Taobao makes me feel that I am a unique customer I believe that Taobao is personalized to my needs
Web personalization	Huang and Zhou, 2018	Mobile shopping	When I use this application, I often adopt 'CAI NI XI HUAN' function ASWP Use After looking through a product, I often adopt 'KAN LE YOU KAN' function
	Krishnaraju et al., 2016	E-government services	Names appeared in Banners Personalized messages were given Product offers were given Personalized offers were given Tailored offers were provided Banner message content enabled quicker task accomplishment Banner message content improved task performance Banner message content enhanced effectiveness Banner message makes task easier Banner messages useful

Consistent with prior works (e.g., Alalwan et al., 2020; Komiak & Benbasat, 2006; Mittal & Lassar, 1996; Srinivasan et al., 2002), a pool of 58 potential scale items (26 items for individual-level personalization, 13 items for social-level personalization, and 19 items for situation-based personalization) was generated. Individual-level personalization consisted of 12 items for the past digital behavior dimension and 14 items for the attitudes & preferences dimension. Similarly, situation-based personalization was composed of 9 time-based personalization items and 10 location-based personalization items. The item pool was generated based on the theoretical domain definitions of the personalization dimensions and measurement scales used in prior research.

After generating the broad item pool, we conducted a three-hour focus group meeting with 4 marketing scholars knowledgeable about personalization practices and scale development. Since the first item pool was as long as possible to hold various sentence forms, several different personalization approaches, and different presenting forms in the literature, we aimed to take opinions of knowledgeable scholars to choose the right sentence or presenting forms and not to miss out any personalization approach. Participants in this meeting, who were briefed about the concept and its potential measurement items, first read the definitions, and then evaluated the relevant items. This initial screening resulted in a total of 50 items remaining in the pool (15 items were eliminated and 7 new items were added). Items that were eliminated were either noted to have similar contents with others in the scale or were likely to be confused with other related concepts in marketing with personalization. For instance, we used various sentence forms in our first pool like "I feel that …", "I believe that….", "I think that….", "The platform personalizes the content based on…". We also have several different presentations in this first pool like using "…" for repetitive parts or writing all sentences without dots. Based on the suggestions of these marketing scholars, we decided to use "The offerings provided me on this platform were created based on …" as sentence form and using dots for repetitive sentence beginnings as presenting form. The seven new items added to the scale involved specific personalization issues that the participants believed to be overlooked in the initial pool. These were about offerings in these platforms (i.e., personalized web interfaces, discounts) or personalization criteria (i.e., individuals' mindset, routines, culture, social groups who are important to them, their social groups' evaluations about products, services and/or brands.).

Next, 15 PhD students and 30 consumers were asked to evaluate the measurement items in terms of fit with domain definitions of the dimensions and sub-dimensions, completeness, repetitions, and clarity. The participating PhD students did have considerable conceptual background in marketing, consumer behavior, organizational behavior, and technology management. Consumers were involved in the study at this phase in order to reflect their unique insights and to make sure that no critical issues from a consumption viewpoint were missed. After eliminating four items that were deemed problematic in terms of clarity and/or found irrelevant by the participants (Four items were about the service providers' information repository who make personalized value offerings, e.g., "The offerings provided me on this platform were created based on the information gathered and used by companies about my past online shopping behaviors / my attitude / my preferences), the item pool was reduced to 46 items.

3.2. Study 2: Initial Purification and Content Validity

To assess content validity (Hair et al., 2009), expert judges including 5 senior faculty members in marketing and 3 experts in technology management who are active in consumer research and familiar with measure development were consulted. Here, we aimed to gain further evaluations of marketing and technology management experts about the related scale. Their expertise in the related fields helped us understand the appropriateness of survey items in terms of both measure development procedures and customer responses toward personalization practices based on technological procedures. The 46-item pool was provided to these experts in a random order and, after explaining the concept of personalization, they were asked to comment on each one of the 46 statements in terms of fit, completeness, redundancy, and clarity. These experts were also asked to match the items with the most appropriate dimension. At least 6 out of 8 majority rules was applied for a group decision to be accepted during these evaluations. After discussing each item individually, the group of experts suggested that 13 items could be eliminated from the pool due to redundancy and ambiguity (e.g., "… based on where I am / what I do.", "… based on what I do in that specific time.", "… based on behaviors of my friends / my family / my social group.", "… based on my digital search history.", "…based on my digital purchase history."). This process therefore resulted in 33 items measuring the first- and second-order dimensions of the multidimensional personalization construct. There were also long discussions about the dimensionalization structure, which ended with consensus on the proposed model.

3.3. Study 3: Further Purification and Content Validity

For further purification, experts from the business world (2 brand managers, 4 digital marketing managers, 2 company managers, 2 digital agency owners) who have experience about personalization practices were consulted. Based on their experience in personalization practices, we aimed to not miss out any personalization approach or method in creating personalized value offerings. After explaining the purposes of the study and the proposed measurement model for personalization, these participants were asked to evaluate the conceptualization and match the item list with specific dimensions/subdimensions of personalization. This panel of practitioners suggested 9 additional items to be eliminated from the scale on the bases of the view that the average respondent could be confused from the wordings and overly technical contents of the items (These items included such terms as 'digital movements', 'digital behaviors', 'online movements', 'online behaviors', 'surrounding environment', 'my/others' attitude towards…"). After this phase, our item pool was reduced to 24. The panel also suggested wordings changes for some of the items.

The items, which were originally developed in Turkish, were then translated into English and retranslated back to Turkish by two separate bilingual individuals. Participants of Study 2 and Study 3 who are competent in both Turkish and English were then asked to evaluate the quality of the translations. After the approval of these panels and a final check by the researchers, both Turkish and English versions of items in the scale were deemed appropriate for further analyses.

3.4. Study 4: Measurement Model Analyses

In this step, the 24-item pool for the multidimensional personalization scale was first subjected to a pilot test using data obtained from 35 undergraduate students who had participated marketing and consumer behavior classes before and was familiar with consumer behavior-related measurements. An exploratory factor analyses of the data did not indicate a problematic issue with regard to the proposed measures, and therefore a broader, face-to-face data collection process was initiated with undergraduate and graduate students from various universities in Turkey since this generation is familiar with such personalized value offerings and has the ability of evaluating such offerings provided to them. To reach students from different regions of the country, the professors from universities in different regions were informed about this study and wanted to make contribution to this study by informing their students, who attended marketing and consumer behavior classes before and were familiar with consumer behavior-related measurements, about participating this part of the scale development procedure in our study. The definition of personalization was first read to the respondents (N = 334) and then they were asked to consider their last experience with a personalization practice and respond to the questionnaire which involved five-point Likert type measurements (1 = strongly disagree and 5 = strongly agree) of the 24 items. The questions also included an "I have no idea" option. Data collection process took approximately two weeks. After the elimination of careless respondents and respondents with too many "I have no idea" remarks, 320 questionnaires remained for analyses. The majority of respondents were women (54.1%) and aged between 18-24 (85%). Based on open ended responses, it was observed that most respondents considered digital platforms as a personalization experience as they provided responses to the items.

An exploratory factor analysis with Varimax rotation was conducted with these data. First, data were subjected to an EFA without setting specific number of factors to extract, and results revealed a five-factor solution (with eigenvalues greater than 1). All but five of the items loaded on the expected factor (dimension or subdimension) as a result of this analysis. The problematic five items were then investigated in further detail in terms of wording and content, and it was decided that all five of them could be eliminated from the measurement process, basically because every single one of them tapped into relatively more specific type of personalization practices (e.g., "… based on my readings on digital platforms in the past.", "… based on my reviews / ratings on digital platforms in the past.", "…based on my preferences about brands / services / digital platforms / shopping in general."). The results of the analyses of the remaining 19 items once again indicated a five-factor solution. As shown in Table 3, in these analyses, (1) all items loaded on the expected factor with loadings greater than 0.50, (2) all item-to-total correlations were above 0.50 and item-to-item correlations were above 0.30 (Spector, 1992), (3) the D-diagonal of the anti-image matrix was above 0.50, KMO = 0.853 ($p < 0.01$), and (4) total explained variance was 66.3%. In addition, each factor had satisfactory Cronbach's alphas ranging from 0.74 for the attitudes & preferences scale to 0.87 for social-level measures. Next, in order to explore the proposed hierarchical structure of the measurement theory, we first forced the number of factors in the solution to three and then conducted additional EFAs to explore the two-dimensional structure of individual-level and situation-based personalization measures (Please see Table 3).

Table 3: Revealed Dimensions Based on Exploratory Factor Analysis

	Factor				
Item	**Past digital behavior**	**Attitudes & preferences**	**Social-level**	**Time-based**	**Location-based**
IPDB2	**.74**	.23	-.02	-.05	.11
IPDB1	**.79**	-.02	.11	.14	.14
IPDB3	**.68**	.50	-.05	-.01	.07
IPDB4	**.72**	.05	.20	.12	-.02
IAP2	.11	**.80**	.18	.15	-.01
IAP3	.15	**.84**	.06	.10	.07
IAP4	.19	**.59**	.39	.02	.10
S5	.03	.13	**.72**	.20	.03
S4	.04	.22	**.62**	.31	.01
S6	.10	.07	**.74**	-.01	.28
S3	.05	-.00	**.77**	.11	.19
S1	.03	.08	**.82**	.08	.17
S2	.11	.15	**.75**	.09	.16
STT2	.03	.02	.22	**.81**	.13
STT1	-.01	.10	.16	**.81**	.23
STT3	.17	.14	.08	**.75**	.11
STL3	.15	.18	.18	.04	**.81**
STL1	.06	.02	.27	.35	**.69**
STL2	.07	.01	.23	.22	**.85**
	Factor				

Item	Individual-level	Social-level	Situation-based
IPDB2	**.72**	-.05	.07
IPDB1	**.61**	.01	.26
IPDB3	**.82**	-.03	.04
IPDB4	**.59**	.11	.14
IAP2	**.58**	.30	.04
IAP3	**.64**	.20	.04
IAP4	**.50**	.47	.03
S5	.09	**.70**	.18
S4	.15	**.62**	.25
S6	.10	**.75**	.18
S3	.02	**.75**	.23
S1	.05	**.81**	.19
S2	.16	**.75**	.18
STT2	.03	.18	**.72**
STT1	.06	.14	**.76**
STT3	.22	.05	**.66**
STL3	.19	.25	**.53**
STL1	.06	.29	**.70**
STL2	.06	.27	**.70**

	Factor	
Item	**Past digital behavior**	**Attitudes & preferences**
IPDB2	**.75**	.17
IPDB1	**.81**	.04
IPDB3	**.68**	.41
IPDB4	**.72**	.14
IAP2	.11	**.84**
IAP3	.15	**.83**
IAP4	.20	**.71**

	Factor	
Item	**Time-based**	**Location-based**
STT2	**.83**	.18
STT1	**.83**	.24
STT3	**.80**	.12
STL3	.05	**.86**
STL1	.34	**.76**
STL2	.22	**.88**

3.5. Study 5: Confirmatory Factor Analyses

At this phase, in order to test the proposed measurement model more rigorously and also to ensure its generalizability, new data were collected via face-to-face administration of the 19-item measure of personalization to a sample of consumers to see their perceptions about perceived value offerings and to also catch evaluations of consumers. To reach these people, researchers used their personal contacts, and the contacts of these people were also gathered. Besides, all these people used social networking platforms to find volunteers in order to participate this survey. These data were subjected to a confirmatory factor analysis (CFA). Similar to the previous data collection, these respondents were also read the definition of personalization and asked to give their responses based on their most recent personalized experience. Initially 282 responses were obtained, but five questionnaires were disregarded due to excessive number of missing responses and the analyses were conducted with a sample of 277 (53.4% male; 55.6% aged between 25-34). Personalization was conceptualized as a reflective construct in the CFAs, based on the notion that the measurement approach is essentially focusing on customer perceptions of firms' personalization attempts and as they are designing personalization approaches firms can actually use several possible combinations of personalization dimensions simultaneously. That is, customer perceptions firms' attempts to develop personalization strategies might reflect upon each and every one of the different dimensions at varying levels. We therefore expect dimensions of personalization to be correlated and believe it is more appropriate to conceptualize the measures to have more of a reflective rather than a formative nature.

A number of alternative models were compared via CFAs at this phase to determine the best fitting measurement structure: (1) the null model ignoring correlations between all variables, (2) a single-factor unidimensional model, (3) the five-factor model with the factors past digital behavior, attitudes & preferences, social-level, time-based, and location-based, and (4) the proposed three-factor second-order model with the factors individual-level personalization (consisting of past digital behavior and attitudes &preferences as second-order factors), social-level personalization, and situation-based personalization (consisting of time- and location-based as second-order factors). Table 4 presents model comparison results based on CFAs.

Table 4: Model Comparison Based on Fit Indices

Model	Chi-Square	d.f.	X^2/d.f.	CFI	TLI	RMSEA	Chi-Square Difference
1	2990.08	171					-
2	1438.81	152	9.47	.54	.49	.18	0
3	347.05	142	2.44	.93	.91	.07	1091.76
4	351.56	145	2.42	.93	.91	.07	4.51

Note: Chi-Square Difference represents the difference the related model with the previous model.

Comparison of the five-factor model and the three-factor hierarchical model does not indicate a statistically or substantively significant difference. Based on the slightly better X^2/d.f. ratio and its theoretical appeal, however, the three-factor hierarchical model (Please see Figure 2) was deemed more appropriate for further investigation. As can be seen through this table, the model fits reasonably well to the observed data (X^2 = 351.56 (d.f. = 145), p < .001; X^2/d.f. = 2.42; RMSEA = .07; CFI = .93; TLI = .91; *** *p* < .001).

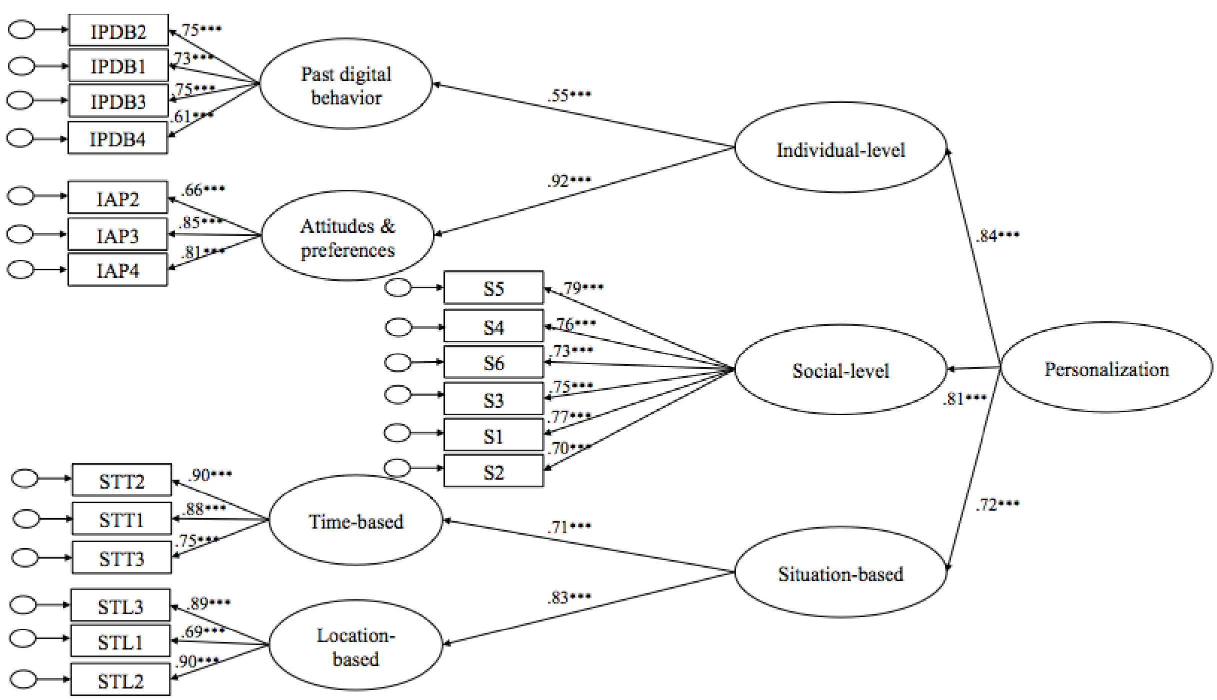


Figure 2: The Three-factor Second-order Model (Model 4)

All factor loadings and AVE estimates are above 0.50, and factor loading estimates range between 0.55 and 0.92, providing evidence for convergent validity (Fornell & Larcker, 1981; Hair et al., 2009). Items with relatively lower factor values (Item 4 of past digital behavior and Item 2 of attitudes & preferences) are observed to tap on relatively rare forms of personalization practices. Next, to assess discriminant validity, the square roots of the AVE estimates for each pair of constructs were compared with the latent factor correlations between the constructs (Fornell & Larcker, 1981). All square roots of the AVE estimates are larger than relevant factor pair correlations, suggesting confirming evidence for discriminant validity. In addition, all Cronbach's alphas and CR scores are above 0.60, thus providing evidence for the internal consistency of the measures (Fornell & Larcker, 1981; Hair et al., 2009; Hu & Bentler, 1995; Nunnally, 1978) (Please see Table 5).

Table 5: Measure Assessment

Construct	Factor Loading	AVE	CR	Cronbach's Alpha
Personalization		.63	.83	.73
Individual-level	.84***	.57	.72	.63
Past digital behavior	.55***			
IPDB2	.75***			
IPDB1	.73***			
IPDB3	.75***			
IPDB4	.61***			
Attitudes & preferences	.92***			
IAP4	.81***			
IAP3	.85***			
IAP2	.66***			
Social-level	.81***	.56	.89	.86
S5	.79***			
S4	.76***			
S6	.73***			
S3	.75***			
S1	.77***			
S2	.70***			
Situation-based	.72***	.60	.75	.69
Time-based	.71***			
STT2	.90***			
STT1	.88***			
STT3	.75***			
Location-based	.83***			
STL3	.89***			
STL1	.69***			
STL2	.90***			

3.6. Study 6: Nomological Validity: Exploring the Outcomes of Personalization

In Study 6, in order to display evidence for the nomological validity of the proposed measurement theory, we explore the effects of the personalization dimensions on some key outcome factors, including (1) positive emotional experience, (2) negative emotional experience, (3) perceived sincerity of the offerings, (4) satisfaction with the experience, and (5) positive behavioral intentions. When customers experience a well-designed personalized service, they encounter options prepared and presented in line with their own preferences and observe that their individual needs are taken into account, thereby promoting feelings of exclusivity, customer involvement and the moment of experience itself (Blasco-Arcas *et al.*, 2013). Accordingly, Koch and Benlian (2015) suggest that feelings of gratefulness are more likely to be aroused when a communication is established through personalized messages. Similarly, prior works have established firmly that personalization increases interactivity, and thereby, promotes feelings of pleasure, arousal, trust, enjoyment, and emotional valence (Fiore et al., 2005; Jiang & Benbasat, 2007; Lee, 2005; Shin et al., 2022). Feelings such as entertainment and irritation are also shown to be affected by personalization practices (Kim & Han 2014). It is therefore reasonable to expect that both individuals' affective reactions and satisfaction judgments would be influenced toward more favorable evaluations as a result of personalized experiences (Ball et al., 2006; Zhu et al., 2022). Furthermore, personalized contents are much likely to establish a connection between marketers and customers, which not only fosters the processing involvement and persuasion likelihood of customers but also reflects upon the perceived sincerity of the offerings (e.g., Petty et al., 2000; van Ooijen, 2022). Ultimately, of course, purchasing intentions and other forms of behavioral intentions are also expected to be influenced positively by personalized purchasing and consumption experiences (Arora et al., 2008; Liu et al., 2021). Indeed, personalization is an important construct in terms of improving customer relationships and enhancing purchase experience (Blasco-Arcas et al., 2013; Kwon & Kim, 2012). Thus, successfully managed personalized experiences would lead to increased positive emotions and sincerity perceptions of the offerings, satisfaction with the experience and intention to use such platforms would be positively influenced and the degree of negative emotions should be diminished.

In order to check for the nature of the aforementioned relationships with the proposed measurement structure, a new set of data was collected. Data were collected via face-to-face administration of the personalization scale and measures of outcome constructs with real life consumers within a four-week period. To reach these respondents, the researchers and their personal contacts searched for new respondents to attend the survey in this process of the study through announcements such as mailing, social media posts, etc. As in the previous data collection processes, respondents were asked to consider a recent consumption experience with some noticeable level of personalization practice. Personalization was measured using the 19-item scale which took its final form in Study 5 (Please see Table 6), and measures of the outcome constructs were adopted from prior research (Please see Table 7). The measures in Pappas et al. (2014) were used to measure positive and negative emotions; perceived sincerity was measured through the scale of Xia (2013); satisfaction scale was adapted from Keaveney and Parthasarathy (2001); and behavioral intentions were operationalized based on the scales used in Johnston and Warkentin (2010) and Venkatesh et al. (2012). Respondents rated all items on five-point Likert scales (1 = strongly disagree and 5 = strongly agree).

Table 6: Personalization Scale

Dimensions-Items	
Individual-level	
Past digital behavior	
IPDB1	The offerings provided me on this platform (personalized web interfaces, discounts, suggestions for products/services, etc.) were created based on (...) my past digital search behaviors.
IPDB2	... my past purchasing behaviors in digital channels.
IPDB3	... my past behaviors on this platform.
IPDB4	... my past behaviors on other digital platforms.
Attitudes & preferences	
IAP2	... my mindset in general.
IAP3	... my philosophy of life.
IAP4	... my lifestyle.
Social-level	
S1	... my social groups.
S2	... social groups which I would or would not like to take part in.
S3	… the preferences of people, who are important to me, about products, services and/or brands.
S4	… the preferences of my friends and family about products, services and/or brands.
S5	… the preferences of people I care about in the matter of products, services and/or brands.
S6	… the preferences of individuals who I follow closely in the matter of products, services and/or brands.
Situation-based	
Time-based	
STT1	... my routines at that time period (working hours, rush hours, etc.).
STT2	... what I did at that moment of the day (working, resting, travelling).
STT3	… the features of that moment.
Location-based	
STL1	... my location (city, country, etc.).
STL2	... my whereabouts (school, workplace, etc.).
STL3	… the features of the place I am in.

Table 7: Scales Used for Nomological Validity

Dimensions-Items	
Positive emotion	
PE1	I feel happy after receiving personalized offerings provided me on this platform.
PE2	I have a warm feeling after receiving personalized offerings provided me on this platform.
PE3	I am being valued after receiving personalized offerings provided me on this platform.
Negative emotion	
NE1	I feel angry after receiving personalized offerings provided me on this platform.
NE2	I am in a bad mood after receiving personalized offerings provided me on this platform.
NE3	I feel upset after receiving personalized offerings provided me on this platform.
Perceived sincerity	
PS1	The offerings provided me on this platform are sincere.
PS2	The offerings provided me on this platform are genuine.
PS3	The offerings provided me on this platform are earnest.
Satisfaction	
SAT1	On the whole, I was satisfied with my experience with that platform.
SAT2	Overall, my positive experience outweighed my negative experience with that platform.
SAT3	In general, I was happy with the experience.
Behavioral intention	
INT1	I intend to continue using the platform in the future.
INT2	I will always try to use the platform in my daily life.
INT3	I plan to continue to use the platform frequently.
INT4	I intend to use the platform in the near future.
INT5	I predict I would use the platform in the near future.
INT6	I plan to use the platform in the near future.

This new sample consisted of 460 consumers (response rate was 80.2 percent). After the elimination of missing and careless responses, 430 questionnaires remained eligible for analyses. The majority of this new sample were female (50.5%) and aged between 25-34 (43%). The most frequently mentioned platforms for a personalized experience in this sample were also digital platforms, most prominent examples including Spotify, Instagram, Twitter, Google, Amazon, Facebook, and Netflix.

Before testing for the nomological validity of the personalization scale, we first evaluated the validity and reliability of the measures involved (Please see Table 8). These analyses confirm the measure assessment results obtained in previous analyses and provide evidence for the validity and reliability of the measures of proposed outcome constructs. Our measurement model has acceptable values for factor loadings and AVE values, indicating the existence of convergent validity (Fornell & Larcker, 1981; Hair et al., 2009). Besides, CR and Cronbach's alpha values confirm reasonable reliability of the scales (Fornell & Larcker, 1981; Hair et al., 2009; Hu and Bentler, 1995; Nunnally, 1978). The square root of AVE values of each construct is larger than the latent factor correlations between the related construct pairs, providing evidence for discriminant validity (Fornell & Larcker, 1981). Moreover, the measurement model fits the observed data reasonably well (X^2 = 1291.0574 (d.f. = 606), $p < .001$; X^2/d.f. = 2.13; RMSEA = .05; CFI = .94; TLI = .93; IFI = .94, *** $p < .001$). Table 9 presents the descriptive statistics and correlation estimates for and between the constructs.

Table 8: Factor Loadings and Estimates for Validity and Reliability

Construct	**Factor Loading**	**AVE**	**CR**	**Cronbach's Alpha**
***Personalization* (PER)**		.62	.83	.73
Individual-level	$.75^{***}$			
Past digital behavior	$.45^{***}$			
IPDB2	$.70^{***}$			
IPDB1	$.67^{***}$			
IPDB3	$.73^{***}$			
IPDB4	$.67^{***}$			
Attitudes & preferences	$.96^{***}$			
IAP2	$.77^{***}$			

IAP3	.87***			
IAP4	.85***			
Social-level	.77***			
S5	.64***			
S4	.66***			
S6	.78***			
S3	.83***			
S1	.88***			
S2	.86***			
Situation-based	.83***			
Time-based	.72***			
STT2	.89***			
STT1	.75***			
STT3	.76***			
Location-based	.80***			
STL3	.86***			
STL1	.70***			
STL2	.85***			
***Positive emotion* (PE)**		.75	.90	.88
PE1	.92***			
PE2	.96***			
PE3	.70***			
***Negative emotion* (NE)**		.74	.89	.89
NE1	.85***			
NE2	.93***			
NE3	.79***			
***Perceived sincerity* (PS)**		.73	.89	.88
PS1	.94***			
PS2	.94***			
PS3	.66***			
***Satisfaction* (SAT)**		.56	.79	.78
SAT1	.79***			
SAT2	.61***			
SAT3	.83***			
***Behavioral intention* (INT)**		.73	.94	.94
INT1	.76***			
INT2	.81***			
INT3	.87***			
INT4	.90***			
INT5	.89***			
INT6	.90***			

*** $p < 0.001$.

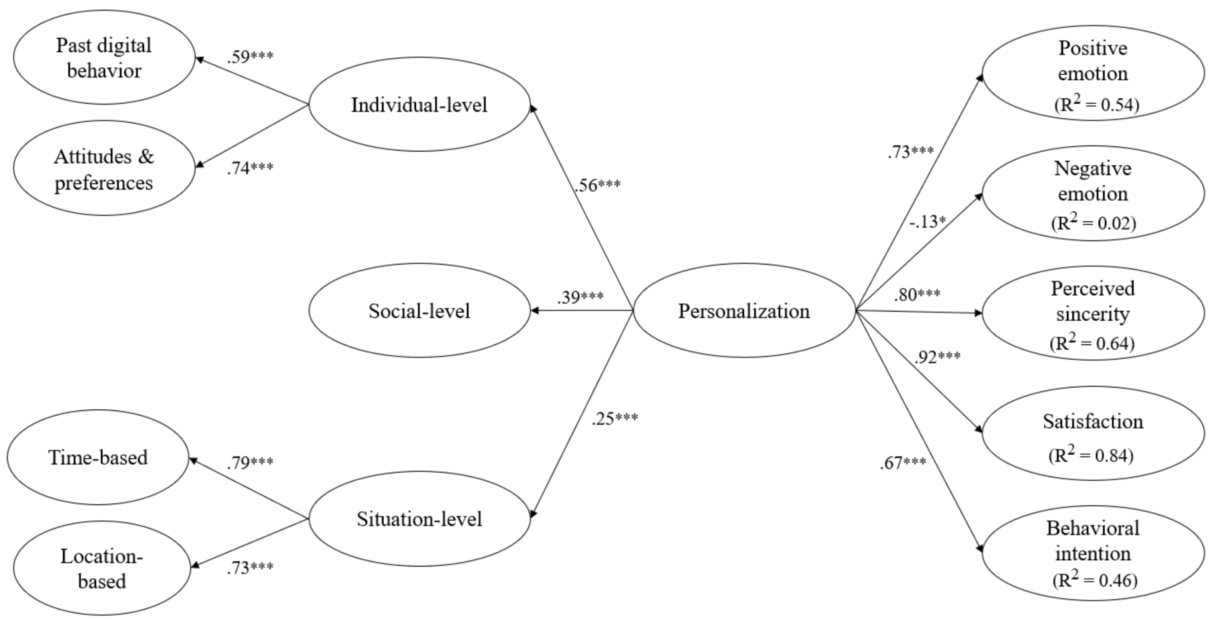
Table 9: Descriptive Statistics and Correlations Estimates

	Mean	SD	1	2	3	4	5	6
PER	3.09	.73	(.78)					
PE	3.54	.98	.313**	(.87)				
NE	1.93	.97	.162**	-.091	(.86)			
PS	3.27	.99	.321**	.605**	-.095*	(.86)		
SAT	3.62	.84	.232**	.545**	-.080	.663**	(.75)	
INT	3.89	.83	.167**	.467**	-.112*	.478**	.604**	(.86)

Notes: Numbers on diagonals indicate square root of AVE. No correlation is greater than the corresponding square root of AVE.
**Correlation is significant at $p < 0.01$ (2-tailed).
*Correlation is significant at $p < 0.05$ (2-tailed).

We also tested for the degree of common method bias and multicollinearity in these analyses using the common latent factor (CLF) analyses (Podsakoff et al., 2003) and variance inflation factor (VIF) estimates. Measurement models with and without the CLF were compared and the differences between standardized path coefficients and fit indices (with CLF: $X^2 = 1248.234$ (d.f. = 605), $p < .001$; X^2/d.f. = 2.06; RMSEA = .05; CFI = .941; TLI = .935; IFI = .941; without CLF: $X^2 = 1291.574$ (d.f. = 606), $p < .001$; X^2/d.f. = 2.13; RMSEA = .051; CFI = .937; TLI = .931; IFI = .937) were shown to be statistically and/or substantively nonsignificant, thus indicating that common method bias may not be a major problem. Similarly, since all VIF estimates were shown to be below 3, problematic degrees of multicollinearity did not exist among the variables in our model.

Finally, Figure 3 displays the parameter estimates of the relationships between personalization dimensions and outcome constructs. The estimated model has acceptable fit indices ($X^2 = 1576.17$ (d.f. = 616), $p < .001$; X^2/d.f. = 2.56; RMSEA = .06; CFI = .91; TLI = .90; IFI = .91, *** $p < .001$) and explains a significant proportion of the variability in satisfaction (84%), perceived sincerity (64%), positive emotions (54%), and positive behavioral intentions (46%). The path leading to negative emotions seems to have the weakest explanatory power (2%). All outcome constructs were allowed to correlate with others in these analyses.



*** $p < 0.001$, * $p < 0.05$

Figure 3: Structural Equation Model with Effects on Outcome Factors

We also tested for the degree of common method bias and multicollinearity in these analyses using the common latent factor (CLF) analyses (Podsakoff et al., 2003) and variance inflation factor (VIF) estimates. Measurement models with and without the CLF were compared and the differences between standardized path coefficients and fit indices (with CLF: $X^2 = 1248.234$ (d.f. = 605), $p < .001$; X^2/d.f. = 2.06; RMSEA = .05; CFI = .941; TLI = .935; IFI = .941; without CLF: $X^2 = 1291.574$ (d.f. = 606), $p < .001$; X^2/d.f. = 2.13; RMSEA = .051; CFI = .937; TLI = .931; IFI = .937) were shown to be statistically and/or substantively nonsignificant, thus indicating that common method bias may not be a major problem. Similarly, since all VIF estimates were shown to be below 3, problematic degrees of multicollinearity did not exist among the variables in our model.

As shown in Figure 3 and Table 10, the effects of the personalization factor on the outcome constructs are all significant and in the expected direction. The expected positive effects of personalization on positive emotions (β, standardized path coefficient = .732; $p < .001$), perceived sincerity ($\beta = .802$; $p < .001$), satisfaction ($\beta = .919$; $p < .001$), and positive behavioral intentions ($\beta = .674$; $p < .001$) are supported. Likewise, personalization is found to influence negative emotions negatively ($\beta = -.127$; $p = .031$). These findings provide strong support for the nomological validity of the proposed multidimensional measurement of personalization.

Table 10: Structural Parameter Estimates

Hypotheses	**Path**	**Standardized Estimates**	***t* value**	**Result**
H1	PER→PE	.732	5.30^{***}	Supported
H2	PER →NE	-.127	-2.15^{*}	Supported
H3	PER →PS	.802	5.38^{***}	Supported
H4	PER →SAT	.919	5.34^{***}	Supported
H5	PER →INT	.674	5.15^{***}	Supported

*** $p < 0.001$, * $p < 0.05$.

4. Discussion

Although personalization is an essential factor for competitive success both for marketing research and practices (Miceli et al., 2007), there are still gaps in marketing research about the conceptualization and operationalization of this complicated practice. In this regard, this study provides several insights with respect to the theory and practice of personalization.

First of all, this study aims to develop a multidimensional measurement tool for perceived personalization by highlighting that the actual personalization and perceived personalization do not always represent the same set of practice (Li, 2016). To do this properly, a complete review of personalization scales in prior research was made and some personalization focuses were revealed. Through this examination, the study uncovers and appreciates the deeper and complex nature of this important issue and also explores the potential personalization dimensions to measure the perception about a broad and complicated personalization strategy. Although we observed some studies focused on one single personalization category (e.g., Ho et al., 2007; Ho & Chau, 2013; Jagadeesan & Subbiah, 2020; Kliman-Silver et al., 2015), we could not see the multidimensional nature of this phenomenon in extant research on personalization (e.g., Desai, 2019; Kwon & Kim, 2012; Zanker et al., 2019) although we always observe multidimensional personalization practices implemented via emerging technologies (e.g., Netflix, YouTube). Despite the fact that current conceptual research and practical examples showed us various focuses to develop a personalization strategy, using all focuses was not a rational way to create a measurement tool. Due to the nature of the focus of "what is personalized", representing a starting point for personalization practices and having an unchangeable nature, this focus was appropriate to conceptualize and operationalize perceived personalization in a mutually exclusive way. Besides, existing conceptualizations and operationalizations (e.g., Srinivasan et al., 2002; Trivedi & Trivedi, 2018; Zhang & Curley, 2018) were further examined based on their focuses while using personalization as a dimension in their research context and appropriateness to cover the prominent aspects of personalization practices in today.

The multidimensional scale developed for the measurement of personalization in the present study expands and develops one-dimensional personalization approaches in prior research and provides a measurement tool that is easy to administer, internally consistent, valid, and adaptable to many product categories, industries, and contexts. Those one-dimensional personalization approaches in prior research (e.g., Ball et al., 2006; Ham, 2016; Kang et al., 2016; Tran, 2017; Tran et al., 2020; Trivedi & Trivedi, 2018; Shanahan et al., 2019) had some specific contexts like mobile applications, banking, advertising, social media and social network sites. However, most personalization studies and practices consist of several different personalization categories, and this broad and complicated nature of phenomenon allow personalization researchers and practitioners to study on the topic in a holistic way. When our scale is compared to previously developed scales, it can be seen through scale items that the current scales in extant research are more related to whether personalization makes one feel special. The multidimensional scale we developed, on the other hand, addresses the individual's perception of personalization in a holistic manner by employing different levels of information. The three levels of information employed are applicable to any company operating in the business world and can thus be used to evaluate individual perception of each personalization application. Therefore, this study proposes a holistic view of personalization that provides an integrated measurement model that could be used in multiple contexts, including digital platforms and more traditional uses of personalization. Besides, this study highlights the importance of the difference between actual personalization and perceived personalization and the value of explaining perceived personalization for consumer behavior and marketing research (Kwon & Kim, 2012; Li, 2016). Therefore, this study provides an effective measurement tool for perceived personalization for academia to capture the technological advancements in this practice by making it possible to measure and evaluate a personalization strategy, which included various dimensions, in a customer-centric way. Furthermore, the rigorous scale development and testing procedures employed in the study leaves little doubt regarding the proposed measurement tool's capability to satisfy scale development criteria psychometrically. The fact that multiple student and consumer samples are used for the validation processes of the scale further enhances its generalizability.

The multidimensional personalization scale developed in this study helps firms to manage their personalized value offering processes in various ways. First, they can find a starting point for the development of a personalization practice by observing the answer to the question 'what is personalized' (i.e., what should we personalize first which will be valuable in the eyes of customers). In this way, they can use this scale in pretesting and evaluating their personalization ideas and based on the results, they can predict how customers would react through the perceptions of them toward the related personalization strategy. Besides, they can gain customer insight and see customer responses starting from understanding customer perception about the related personalization practice since customers' perceptions is the key issue for the competitive success of the related practice (Miceli et al., 2007; Strycharz et al., 2019). Hereby, they can use the scale for assessment and tracking purposes and test the functionality of their personalization applications.

This study also explores the key outcomes of perceived personalization in different empirical settings. Our tests for the nomological validity of the personalization scale also provide novel insights regarding the potential impacts of personalization practices on critical outcome constructs of (1) positive emotional experiences, (2) negative emotional experiences, (3) perceived sincerity of the offerings, (4) satisfaction with the experience, and (5) positive behavioral intentions. Findings from the analyses indicate that personalization practices seem to have the strongest positive effect on customer satisfaction, followed by perceived sincerity of the offerings, positive emotional experiences, and positive behavioral intentions. The observed negative effect of personalization on negative emotional experiences seems to be substantively less important yet still statistically significant. While expanding existing research about the role of personalization in gaining desired outcomes related to consumer responses toward such practices (e.g., Arora et al., 2008; Ball et al., 2006; Blasco-Arcas et al., 2013; Jiang & Benbasat, 2007; Kim & Han 2014; Petty et al., 2000), there is no doubt that these observations about predicted relationships would imply important insights for both theoreticians and managers designing personalization practices. Each personalization strategy may have a different impact on wide variety of performance outcomes, and, furthermore, such effects are likely to vary substantially across different consumer groups and product categories. Therefore, much needs to be done in this area to reveal the real impacts personalization practices on the attitudinal and behavioral responses of customer by academia and practitioners.

5. Limitations, Future Research Directions, and Conclusion

One possible limitation of the findings in the present study is that, although the measures utilized that are developed for general use in both digital and traditional applications of personalization, most of the respondents seem to have considered a recent experience with digital platforms as they responded to the questions. This should be expected, of course, since most people are having personalization experiences predominantly at digital platforms nowadays, and yet it is still necessary to have concerns about the generalizability of the findings beyond digital contexts. In fact, to the extent that the proposed model could be utilized in different personalization contexts, including personalization of marketing practices for products, services, or distribution processes; or personalization of different experiences such as movies, music streaming services, or games, the value of the proposed model would be confirmed. Furthermore, the question of which specific personalization strategies would contribute to specific contexts (i.e., tourism and hospitality, social media, electronic commerce, online shopping, mobile shopping, etc.) certainly encompasses a critical issue for future research. The proposed model could also be utilized to reveal the long-lasting effects of perceived personalization toward the related practices (e.g., effects on brand equity, customer engagement, customer citizenship behavior, loyalty, etc.), an avenue for future research that obviously represents a critical gap and poses great theoretical and practical relevance.

Finally, it is also important to note that the proposed personalization taxonomy is based on only one of the possible classification criterions (i.e., what is personalized). We focused on the personal level information which will be used in the development of personalized value offerings to customers here. Future research focusing on classifications of personalization approaches that rely on multiple criterions, specifically including the qualities and other aspects of the means through which personalization practices are realized (i.e., focusing on the presentation and personalizing the presenting way, the communication with the customer), should definitely open new and fruitful areas for future researchers to pursue.

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