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Piloting personalization research through data-rich environments: a literature review and future research agenda

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Abstract

Purpose – Over the last 50 years, increased attention for personalization paved the way for one-to-one marketing efforts, but firms struggle to deliver on this promise. The purpose of this manuscript is to provide a complete picture on personalization, develop a future research agenda and put forth concrete advice on how to move the field forward from a theoretical, methodological, contextual, and practical viewpoint.

Design/methodology/approach – This research follows a systematic literature review process, providing an in-depth analysis of 135 articles (covering 184 studies) to distill the (1) key building blocks and components of personalization and (2) theoretical, contextual, and methodological aspects of the studies.

Findings – This manuscript uncovers six personalization components that can be linked to two personalization building blocks: (1) learning: manner, transparency, and timing and (2) tailoring: touchpoints, level, and dynamics. For each of these components, the authors propose future research avenues to stimulate personalization research that accounts for challenges in today's data-rich environments (e.g. data privacy, dealing with new data types). A theoretical, methodological, and contextual (i.e. industry, country and personalization object) review of the selected studies leads to a set of concrete recommendations for future work: account for heterogeneity, embed theoretical perspectives, infuse methodological innovation, adopt appropriate evaluation metrics, and deal with legal/ethical challenges in data-rich environments. Finally, several managerial implications are put forth to support practitioners in their personalization efforts.

Originality/value – This research provides an integration of personalization research beyond existing and outdated review papers. Doing so, it accounts for the impact of new technologies and Artificial Intelligence and aims to advance the next generation of knowledge development on personalization.

Keywords Personalization, Individualization, One-to-one marketing, Systematic literature review, Consumer experience, Technology, Digital

Paper type Literature review

AQ: 6

Introduction

Personalization entails *tailoring (part of) the marketing mix such as promotions, price, and product recommendations to the consumer* (Bleier *et al.*, 2018; Libai *et al.*, 2020) and fits within the overall market trend to individualize touchpoints between consumers and firms in data-rich environments. The idea of personalization has been around for a long time and manifested itself in various ways like store employees greeting consumers differently (Neuhofer *et al.*, 2015; Surprenant and Solomon, 1987) and sending electronic communication

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with a personalized heading (Pfiffelmann *et al.*, 2020; Sahni *et al.*, 2018). Personalization sets itself apart from other individualized marketing efforts like customization, in that the firm takes control of and decides on how to adapt a specific touchpoint to consumers, rather than consumers taking the lead (Bleier *et al.*, 2018).

Recent technological advances (e.g. Internet-of-Things (IoT) and Artificial Intelligence (AI)) and access to new data types (e.g. clickstream data and biometrics) have spiked organizational interest in and consumer demand for personalized interactions and offerings (Kumar *et al.*, 2019), even to the extent that it has become a new norm in service delivery (Jaakkola and Terho, 2021). Examples of highly personalized service are manifold, including Spotify pushing playlists tailored to its individual users and online apparel retailer Stitch Fix leveraging data analytics to deliver personalized styling packages. A study by Harvard Business Review Analytic Services (2018) finds 80% of managers today say personalization is key to their organization's strategy, while Accenture (2018) finds 91% of consumers indicating they are more likely to shop with brands and firms that offer for personalized service.

Personalization efforts, however, also come with a series of challenges such as managing big data and algorithms, data integration and accessibility, dealing with privacy concerns, and adhering to regulatory frameworks like Europe's General Data Privacy Regulation (GDPR) (Aguirre *et al.*, 2016; Bang *et al.*, 2019; Longoni *et al.*, 2019; Riegger *et al.*, 2021; Tran *et al.*, 2020b; Yun *et al.*, 2021). Moreover, consumers may not always embrace personalization due to privacy concerns and perceived intrusiveness (e.g. Morimoto, 2020; Pfiffelmann *et al.*, 2020), despite its potential to nurture intimate and meaningful relationships with firms (Chung *et al.*, 2016; Murray and Häubl, 2009) and its positive impact on consumer experience and perceived value (Bang *et al.*, 2019; Wedel and Kannan, 2016). This makes managers face significant uncertainties when developing, implementing, and executing their personalization strategies (Kumar *et al.*, 2019).

To date, scholars have devoted significant attention to the topic of personalization to support managerial practice. Although several reviews of these scholarly efforts exist, existing personalization review papers are limited in at least four ways – see Table 1 for an overview. *First*, several reviews have sought to conceptualize personalization in an ad-hoc manner through a selected (instead of a structured) literature review process. This makes that the suggested conceptualizations do not identify all relevant components of personalization. A more detailed understanding, however, may bring much needed granularity so that managers are in a better position to understand where they can direct their efforts toward and researchers may develop a more complete view on personalization. *Second*, other (structured) reviews focus on specific settings such as e-commerce (i.e. Adolphs and Winkelmann, 2010; Salonen and Karjaluoto, 2016) and advertising (i.e. Boerman *et al.*, 2017), discuss the implementation challenges that come with personalization (i.e. Fan and Poole, 2006), outline the difference between personalization and customization (i.e. Arora *et al.*, 2008; Sunikka and Bragge, 2012) and provide some general directions for future work (i.e. Montgomery and Smith, 2009), but lack a comprehensive integration of personalization knowledge to develop an in-depth understanding of personalization. *Third,* as new technologies and AI are pushing the practice of personalization to new heights, new opportunities and challenges arise that have not yet been covered in the literature. Most reviews date 10 years or more back, with the most recent one being from 2017 and only focusing on advertising (Boerman *et al.*, 2017). Guidance is needed as to where the field should be moving if it intends to keep pace with the rapidly evolving practitioner space. *Fourth*, none of the existing review papers considers the theoretical, contextual, and methodological characteristics of personalization studies, leading to an incomplete assessment of the state of the art of the field and failing to comprehend how it may enhance its impact on practice. T1

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Table 1. Personalization review studies

Study	Goal	Key findings	Review depth: *Selected vs Structured*	Review depth: *Review of TCM information*[a]	Identification of personalization components	Research focus
Murthi and Sarkar (2003)	Conceptualization of the personalization process and its strategic role in interactions between the firm and other key players in the firm's value system	Identification of the personalization process composed of three stages – learning, matching and evaluation	Selected	Absent	Limited	Online environments
Fan and Poole (2006)	Conceptualization of personalization and its implementation	Identification of 4 different schools of thought underlying personalization, and the introduction of a personalization implementation classification scheme (what? to whom? who does?)	Structured ($n = 142$)	Absent	Limited	Online and offline environments
Vesanen and Raulas (2006)	Conceptualization of the personalization process and its hurdles	Identification of the personalization process composed of different phases – consumer interactions, analyses of consumer data, customization based on consumer profiles, targeting of marketing activities – and overview of hurdles to its execution	Selected	Absent	Limited	Online and offline environments

(*continued*)

Table 1.

Study	Goal	Key findings	Review depth: *Selected vs Structured*	Review depth: *Review of TCM information*[a]	Identification of personalization components	Research focus
Vesanen (2007)	Conceptualization of the personalization process	Identification of the personalization process composed of different phases – consumer interactions, analyses of consumer data, customization based on consumer profiles, targeting of marketing activities – and its benefits and costs for the consumer and firm	Selected	Absent	Absent	Online and offline environments
Arora *et al.* (2008)	Summarize key challenges and knowledge gaps in the personalization-customization environment	Differentiation between personalization and customization, and summary of research opportunities	Selected	Absent	Absent	Online and offline environments
Montgomery and Smith (2009)	Review of personalization literature	Debate about the various topics underlying personalization research (i.e. definition, framework, methodology for implementation, and effectiveness), and an outline of topic relevant to online personalization	Selected	Absent	Absent	Online environments
Adolphs and Winkelmann (2010)	Review of personalization literature in e-commerce	Identification of three main research categories in e-commerce: implementation, theoretical foundations, and user centric aspects	Structured ($n = 42$)	Absent	Absent	Online and offline environments

(*continued*)

Table 1.

Study	Goal	Key findings	Review depth: *Selected vs Structured*	Review depth: *Review of TCM information*[a]	Identification of personalization components	Research focus
Sunikka and Bragge (2012)	Review of personalization and customization literature	Differentiation between personalization and customization, and overview of main research categories	Structured ($n = 2,427$)	Absent	Absent	Online and offline environments
Salonen and Karjaluoto (2016)	Review of literature on web personalization	Identification of three main research categories in e-commerce: implementation, theoretical foundations, and user centric aspects	Structured ($n = 91$)	Absent	Absent	Online environments
Boerman *et al.* (2017)	Review of literature on personalization in advertising	Identification of framework for online behavioral advertising	Structured ($n = 32$)	Absent	Absent	Online environments (advertising)
This study	*Review of personalization literature to conceptualize its components along with the theoretical, contextual, and methodological foundations*	*Identification of personalization components that constitute two building blocks: learning (manner, transparency, timing) and tailoring (touchpoints, level, dynamics)*	Structured ($n = 135$)	Present	Present	Online and offline environments

Note(s): [a]TCM stands for theoretical, contextual and methodological

To address current shortcomings, the research aim is fourfold. *First*, we aim to provide a complete and updated picture of what personalization entails based on a structured literature review of 135 papers (covering 184 studies). We thereby unravel two key building blocks of personalization and their respective components: – (1) learning (manner, transparency, and timing) and (2) tailoring (touchpoints, level, and dynamics). Doing so allows us to bring much needed granularity and integration to the field (Vesanen and Raulas, 2006) [1], and moves beyond earlier incomplete conceptualizations of personalization to support researchers and managerial practice. *Second*, building on the gained insights and current trends, we outline a comprehensive future research agenda to stimulate further personalization research that is in line with and addresses current challenges (e.g. data privacy, new data types) in today's data-rich environment. *Third*, building on the identified theoretical, contextual, and methodological aspects of personalization research, we also put forth concrete practical advice for academic research. Specifically, we detail how personalization research should account for heterogeneity, infuse methodological innovation, embed theoretical perspectives, adopt appropriate evaluation metrics, and determine ways to deal with (upcoming) legal/ethical challenges to preserve consumer privacy (e.g. GDPR and Federated Learning of Cohorts). These considerations may enhance the impact personalization research may have on business practice. *Fourth*, we stipulate several recommendations for practice building on our conceptualization of personalization.

The remainder of this paper is organized as follows. First, we detail the methodology and protocols adopted for the systematic literature review. Next, we provide a detailed discussion on the key building blocks of personalization and their respective components. Third, we outline various avenues for future research. Finally, we offer concrete theoretical, contextual and methodological advice to enhance the impact of future work and discuss the managerial implications of our work.

Methodology

To unravel the key components of personalization in combination with the theoretical, methodological, and contextual foundations of this research stream and determine initial avenues for future research and practice, we performed a systematic review of the personalization literature. Doing so, we relied on the guidelines of Snyder (2019) and Tranfield *et al.* (2003). This review approach involved two stages: (1) literature search and selection of the studies, and (2) data extraction and synthesis. The selection protocol for this systematic review is detailed in Figure 1. F1

Literature search and selection

We sourced the articles from Web of Science, because it provides a comprehensive portfolio of business, management, and information systems journals. To guarantee objectivity, transparency, and replicability of our bibliographic search, we followed a five-step procedure recommended by Kranzbühler *et al.* (2018). As visualized in Figure 1, we first identified the most common keywords used by leading publications in the field. These formed the basis for our search string. Specifically, we searched for articles containing the words "personalization" or "personalisation" or "personalized" or "personalised" in their title, abstract or author keywords. This keyword search resulted in 90,662 articles, covering the 1972–March 2021 timeframe. Second, we limited our selection to peer-reviewed, academic journals in English to increase the relevance and quality of our results set. Abstracts of published items, books, book reviews, discussions, commentaries, editorial material, and proceeding papers were excluded. Also, the results were further refined with respect to subject category. Articles published under the Web of Science category of "Business" and "Management" were included. All this refinement

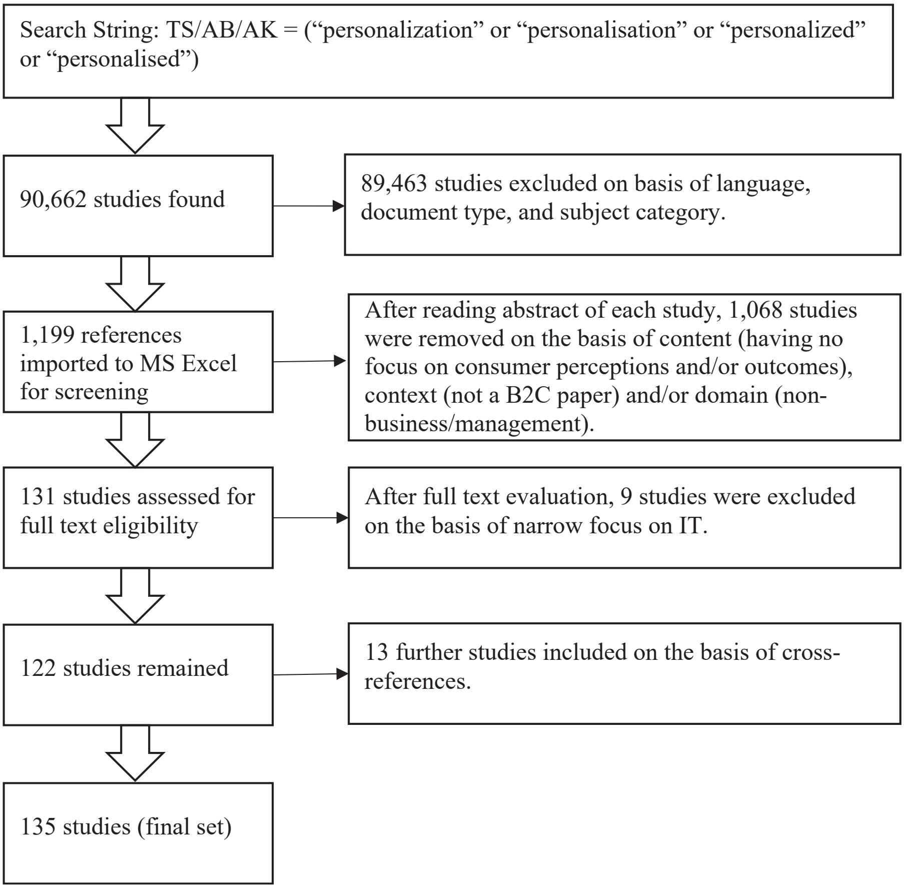
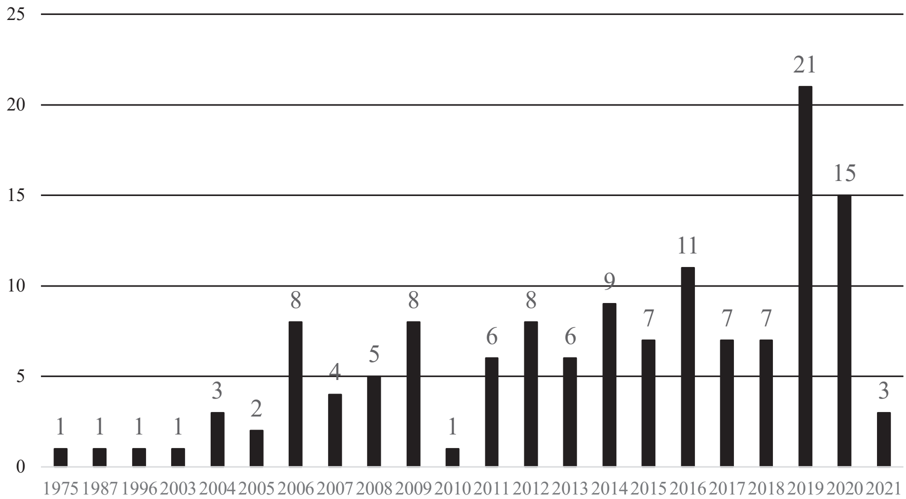


Figure 1.
Literature selection process

resulted in 1,199 articles. Third, we performed a thorough screening of these articles. The initial examination of the identified publications indicated that there were redundant entries, as many did not relate to the scope of this study. The authors read the abstract of all articles in the pool, filtering each against two criteria: (1) having a focus on consumer perceptions and/or outcomes of personalization (e.g. articles focusing on the development of novel personalization algorithms or the IT infrastructure needed for personalization were kept out of the sample as they lacked consumer/outcome focus) and (2) having a focus on personalization in a B2C context. This resulted in a set of 131 papers. Fourth, the full text of the remaining articles was read, causing 9 additional articles to be excluded based on a too narrow focus on IT. Finally, cross-references
F2 led to the inclusion of 13 additional articles, resulting in a final set of 135 articles. Figure 2 provides more insights in the spread of articles over the years. Web Appendix 1 and 2 provide an overview of respectively the included articles and the number of articles per journal.

Data analysis and synthesis

In line with Moeller *et al.* (2013), the analysis of the selected articles involved five steps: familiarizing with the articles, coding article content, categorizing codes/categorizations, and further analyzing. This content analysis started with the aim of gaining a basic



Note(s): Analysis was done in March 2021, explaining the lower number in 2021

Figure 2. Number of personalization articles per year

understanding of the selected literature, followed by *in vivo* coding of the conceptualization of personalization and the identification of first-order codes. Next, the authors independently grouped these first-order codes into second-order categories and subsequently compared these categories with one another. Inconsistencies were resolved through discussion among the author team. Finally, the six remaining second-order categories were labeled as "components" and grouped into third-order categories denoted as "key building blocks" (see coding tree in Web Appendix 3 – for more detailed coding see Web Appendix 4). The key building blocks were labeled as learning (components: manner, transparency, and timing) and tailoring (components: touchpoints, level, and dynamics) (see Table 2 for definitions and descriptions of these concepts). In addition to these steps T2 aimed at outlining the conceptualization of personalization (i.e. what personalization entails), theoretical (i.e. on what theories was the research built?), methodological (i.e. how was study data collected?), and contextual (i.e. in what country/industry was data collected? What was the object of personalization?) data of every separate study in all articles were coded. In what follows, we will first look at personalization in more detail and outline its conceptual dimensions (i.e. what does personalization entail?). Next, we outline a comprehensive future research agenda related to the personalization building blocks and their respective components, considering today's data-rich business environment. Finally, we discuss how this research agenda may be achieved and what theoretical, methodological, and contextual updates are needed. We conclude the paper with some implications for practice.

Personalization: building blocks and components

To address the first goal of this study – providing a comprehensive conceptualization of personalization – we draw on structured literature analysis. This analysis identified learning and tailoring as two common and overarching building blocks of personalization, which we define respectively as (1) the extraction and collection of consumer preference data during consumer-firm interactions and its transformation into useable input for

Key building blocks (third-order categories)	Components (second-order categories)	Components (first-order codes)	Number of articles	% (out of 135 articles)
Learning = *the extraction and collection of consumer preference data during consumer-firm interactions and its transformation into useable input for personalization*	Manner (n = 56–41.5%) = *the way in which consumers are involved in gathering data about their preferences and needs*	Explicit = *firm asks consumers to express their general preferences/needs as input to consumer profile building*	17	12.6%
		Implicit = *firm collects data and infers preferences/needs from actual behavior (e.g, monitoring browsing patterns)*	10	7.4%
		Both	29	21.5%
	Transparency (n = 17–12.6%) = *how open a firm is about its data collection and processing*	Overt = *consumers are aware of how their data is being collected, used, stored and potentially shared with other parties*	8	5.9%
		Covert = *consumers are not aware of how their data is used, stored and shared (consumer may even not be aware data is collected)*	0	0.0%
		Both	9	6.7%
	Timing (n = 67–49.6%) = *the moment of data collection and interpretation*	Real-time = *collection and interpretation of data during consumer journeys as they take place*	9	6.7%
		Retrospective = *reconnection to data collected during previous consumer-firm interactions and interpreting after firm-consumer interactions*	38	28.1%
		Both	20	14.8%
Tailoring = *transforming what the firm has learned about consumers through data collection and interpretation into the actual design of individualized solutions*	Touchpoint (n = 102–74.5%) = *what consumer touchpoints are tailored to consumer preferences*	Digital = *adaptation of digital touchpoints to consumer preferences*	77	57.0%
		Human = *adaptation of frontline employee interactions to consumer preferences*	6	4.4%
		Physical = *adaptation of real-world objects to consumer preferences*	4	3.0%
		Digital/Human/Physical	2	1.5%
		Digital/Human	3	2.2%
		Digital/Physical	9	6.7%
		Human/Physical	1	0.7%
	Level (n = 100–74.1%) = *the specificity by which an offering is tailored to the preferences of consumers*	Low = *adaptation of consumer-firm touchpoints at segment-level or basic individual-level (e.g. adapting email heading)*	1	0.7%
		High = *adaptation of consumer-firm touchpoints to strongly match individual consumers*	57	42.2%
		Both	42	31.1%
	Dynamics (n = 83–61.5%) = *the extent to which personalized offers build on real-time or historical information*	Adaptive = *adaptation of touchpoints based on historical information*	13	9.6%
		Static = *adaptation of touchpoints based on real-time data*	60	44.4%
		Both	10	7.4%

Table 2.
Key building blocks in personalization research

personalization and (2) transforming what the firm has learned about consumers through data collection and interpretation into the actual design of individualized solutions. As a matter of fact, these building blocks are reflected in descriptions of personalization as processes in which firms decide upon the most suitable marketing mix for individual consumers based on the consumer data collected previously or in real-time (Arora *et al.*, 2008; Chung *et al.*, 2016). These building blocks distinguish personalization from customization defined as a process where a consumer proactively decides themselves upon the elements of their desired marketing mix (Arora *et al.*, 2008; Bleier *et al.*, 2018). Personalization research further connects these two building blocks as forming distinct phases of a personalization process (Li, 2019; Piccoli *et al.*, 2017). Here, learning through data collection and interpretation happens and then serves as input for the actual tailoring of the consumer-firm encounter (i.e. adapted products, communication, etc.). Moreover, several authors also emphasize a cyclical process by which the outcomes of the tailoring process are fed back into the learning, to enhance the outcomes of personalization efforts (Adomavicius and Tuzhilin, 2005; Chung *et al.*, 2016; Neuhofer *et al.*, 2015). In what follows, we elaborate upon the learning and tailoring building blocks by detailing their components. Table 2 details how strongly each component has been discussed in the literature.

The learning building block of personalization

The learning building block of personalization includes the combination of gathering data about consumers and processing these data to gain insight into consumers' preferences (Adolphs and Winkelmann, 2010). Building on the coding process, we identify three components underlying learning: manner of learning, transparency of learning, and timing of learning.

Manner of Learning reflects the way in which consumers are involved in gathering data about their preferences and needs, as consumer data can either be collected *explicitly* or *implicitly* (Piccoli *et al.*, 2017). In case of explicit learning, the firm asks consumers to express their general preferences and needs as input to consumer profile building, without necessarily mentioning the purpose of the data collection. With implicit learning, the firm collects consumer data and infers preferences from actual behavior (e.g. monitoring browsing patterns) (Liang *et al.*, 2006) with consumers not necessarily being aware of the collection and its purposes (Wattal *et al.*, 2012). In this regard, firms can use tracking technologies such as first-party cookies (Salem *et al.*, 2019) or rely upon third-party cookies (Boerman *et al.*, 2017) to gather personal information. As shown in Table 2, 41.5% ($n = 56$) of the 135 articles in our set refer to manner of learning (21.5% refer to both manners of learning, 12.6% only to explicit learning, and 7.4% only to implicit learning).

As explicit learning relies on active consumer input, it may place a burden of time and effort on consumers that may be undesirable (Glushko and Nomorosa, 2012; Gretzel and Fesenmaier, 2006). Also, consumers may sometimes not be able to provide the necessary information (Piccoli *et al.*, 2017). Moreover, consumers may deliberately provide inaccurate information in attempts to secure their privacy or sometimes not be able to provide accurate information (Chung *et al.*, 2009; Glushko and Nomorosa, 2012). Implicit learning, in turn, requires no time or effort of consumers, but may violate consumer privacy perceptions (Kubicka, 2016) because consumers may lack knowledge about cookies even though firms inform users about their application (Strycharz *et al.*, 2019). As such, higher perceptions of intrusion into one's personal life may emerge (Aguirre *et al.*, 2016) along with lower consumer satisfaction and reduced behavioral intentions (Taylor *et al.*, 2009). These negative consumer outcomes of privacy concerns do not emerge in case of explicit learning, as consumers perceive higher levels of control on what data is collected (Taylor *et al.*, 2009). In a similar vein, extant research further shows that implicit learning often reduces trust (Aguirre *et al.*, 2016), whereas explicit learning enhances trust (e.g. Wang and Benbasat, 2016). In practice, a combination of both methods is often used with explicit learning as a way to obtain general information on consumers and/or their preferences and implicit learning as a way to refine this information (Piccoli *et al.*, 2017).

Transparency of Learning relates to how open a firm is about its data collection and processing. Consumer data can be collected and used in an *overt* way, where individuals are aware of how their data is being collected, used, stored, and potentially shared with other parties (Aguirre *et al.*, 2015; Awad and Krishnan, 2006) and may exert some level of control over their data (e.g. through explicit consent). Conversely, consumer data may also be used in a *covert* way, where individuals are not aware of how their data is used, stored, and shared (consumer may even not be aware data is collected) (Boerman *et al.*, 2017). As shown in Table 2, only 12.6% ($n = 17$) of the articles in our literature review focus on transparency (6.7% focuses on both covert and overt learning, 5.9% on overt learning and 0.0% on covert learning only).

Advocates of covert learning claim that consumers benefit if data collection methods do not disrupt the consumer experience (Aguirre *et al.*, 2015), but covert learning can be harmful and unethical (Boerman *et al.*, 2017). Consumers may feel spied by unknown tracking of their information by firms (Aguirre *et al.*, 2015). If firms intrude into consumers' lives, negative emotions may emerge (Smink *et al.*, 2020) and their behavioral intentions toward the firm may decrease (e.g. Gironda and Korgaonkar, 2018). Conversely, firms that opt for overtly informing consumers about their data collection and processing may increase consumers' positive behavior (e.g. click-through rates) (Aguirre *et al.*, 2015; Boerman *et al.*, 2017). Providing consumers with transparency and control over their information reduces their privacy concerns (Awad and Krishnan, 2006; Song *et al.*, 2016), and perceived risks (e.g. privacy concerns and feelings of intrusiveness) (Van Den Broeck *et al.*, 2020), enhances trust (Wang and Benbasat, 2016), effectiveness (i.e. attitude, satisfaction, purchase intention and recommendation intention toward the service provider) (Kim *et al.*, 2019a) and benefits (e.g. relevance of the ads and convenience) (Van Den Broeck *et al.*, 2020) and increases purchase intentions (Tucker, 2014). Further, transparency during learning has been shown to positively affect perceived fit of the personalized offers (Gretzel and Fesenmaier, 2006).

Timing of Learning relates to the moment of data collection and interpretation, by which we may discern between real-time and retrospective learning. *Real-time learning* involves the collection of data during consumer journeys as they take place and its immediate usage for personalization, whereas *retrospective learning* implies reconnecting to data collected during previous consumer-firm interactions and interpreting after firm-consumer interactions (e.g. analyzing and interpreting one's collected purchase history or web surfing patterns over time) (Dantas and Carrillat, 2013; Thirumalai and Sinha, 2009). 49.6% ($n = 67$) of the articles in our set refer to timing of learning (28.1% focuses on retrospective learning only 6.7% focuses on *real-time learning*, and 14.8% considers the combination – see Table 2).

Recent research suggests that real-time learning can help firms to dynamically anticipate and address consumer needs at every step along the consumer journey, thereby generating better matches between consumer preferences and firm offerings (Neuhofer *et al.*, 2015). Similarly, Aguirre *et al.* (2015) argue that firms should minimize the time between gathering information about consumers' preferences and their usage and preferably gather information in real-time. Consumers' past preferences are often not a good predictor of their future preferences due to possible changes in consumer status, mind, and taste (Simonson, 1990). In practice, firms often combine retrospective and real-time learning to tailor their offerings to consumer preferences and needs, thus delivering a targeted solution to the consumer (Thirumalai and Sinha, 2009).

The tailoring building block of personalization

The second building block – tailoring – involves transforming what the firm has learned about consumers through data collection and interpretation into the actual design of individualized solutions (Murthi and Sarkar, 2003). The better organizations know their consumers (through learning), the better they can tailor their offerings to their consumers (Shen and Ball, 2009). For tailoring, we can distinguish three components: (1) touchpoint, (2) level, and (3) dynamics.

Tailoring Touchpoint refers to what consumer touchpoints are tailored to consumer preferences. More particularly, we discern digital, physical, and human touchpoints. *Digital tailoring* involves adapting technology-driven touchpoints like emails (Sahni *et al.*, 2018; Song *et al.*, 2016), electronic/mobile news/newsletters (Chung *et al.*, 2016; Dantas and Carrillat, 2013), online interactions (Thirumalai and Sinha, 2009; Pappas *et al.*, 2016), websites (Benlian, 2015; Nath and Mckechnie, 2016), and mobile apps (Guo *et al.*, 2016; Kang and Namkung, 2019). When it relates to online or mobile channels, firms can achieve digital tailoring through personalized promotions, including personalized offers and coupons (Pappas, 2018; Wierich and Zielke, 2014), personalized recommendations (Whang and Im, 2018), programmatic advertising (i.e. aligning their content with consumer attributes to achieve digital tailoring – Deng *et al.*, 2019) or location-based advertising (i.e. aligning the promotion with the consumers' geographic position – Bang *et al.*, 2019). Location-based advertising is labeled as geo-fencing when a consumer is within the vicinity of the promoting firm, whereas geo-conquesting occurs when firms apply this locational tailoring to the competitors' locations (Tong *et al.*, 2020). *Physical tailoring* refers to matching physical objects in the offline world to consumers' preferences, as illustrated by personalized products (Lee *et al.*, 2011; Thirumalai and Sinha, 2009) and personalized mail surveys (Mccoy and Hargie, 2007). *Human tailoring* refers to employees who match offerings and interactions to consumers preferences during the service encounter and experience creation (Leischnig *et al.*, 2018; Neuhofer *et al.*, 2015). As shown in Table 2, 74.5% ($n = 102$) of the articles focus on touchpoint tailoring, with a dominant focus on digital touchpoints (57%). While human (4.4%) and physical (3.0%) tailoring have been around long before digital tailoring, they are surprisingly underrepresented in personalization literature (Koch and Benlian, 2015; Montgomery and Smith, 2009).

So far, only few studies compare the consumer outcomes of tailoring different types of touchpoints and findings vary. Thirumalai and Sinha (2013), for instance, show that providing consumer aid in decision making in an online purchasing context (digital touchpoint) is less desirable in terms of establishing loyalty to the firm than offering personalized delivery of the order. This is because delivery services have a physical touchpoint (delivered package) and sometimes also a human touchpoint (deliverer). Conversely, Glushko and Nomorosa (2012) – who compared human and digital tailoring to identify the capabilities needed to personalize a service encounter – show that human tailoring is not essential to generate better consumer experiences. In fact, very sophisticated consumer information systems that keep track of explicit and implicit guest preferences in hotels may outperform tailoring done by hotel front desk clerks. Wattal *et al.* (2012), in turn, argue that personalization of physical touchpoints – such as a specific product – has a more positive impact on consumer behaviors than personalizing communication via digital touchpoints.

Tailoring Level relates to the specificity by which an offering is tailored to the preferences and needs of consumers. Several studies in our literature review go beyond juxtaposing tailored vs untailored offerings and propose that firms can decide upon the level of tailoring (e.g. Kwon and Kim, 2012; Thirumalai and Sinha, 2009). Specifically, we may distinguish between low vs high levels of tailoring. Here, a *low tailoring level* refers either to adapting offerings to preferences of consumer segments denoted as group-level personalization (Bang *et al.*, 2019), which has also been labeled as one-to-N personalization (Bleier *et al.*, 2018) or using a little amount of distinctive personal information only for tailoring personalized solutions (Zarouali *et al.*, 2019) – e.g. addressing a consumer by name in a further generic email. A *high tailoring level* occurs either when offerings are tailored to individual preferences (Bang *et al.*, 2019), which is also denoted as one-to-one personalization (Bleier *et al.*, 2018) or when tailored solution convey highly distinctive knowledge of consumers' personal characteristics and preferences (Zarouali *et al.*, 2019). As shown in Table 2, 74.1% ($n = 100$) of the articles incorporate tailoring level, with a dominant focus on high tailoring levels (42.2–31.1% focuses on the low/high combined, 0.1% of studies on low only).

Extant studies suggest that higher tailoring levels are more effective and are positively associated with consumers' positive attitude toward personalized offers (Bang *et al.*, 2019), lower choice evaluation cost (Nath and Mckechnie, 2016), increased ratings (Zhang *et al.*, 2020), and consumer satisfaction (Decock *et al.*, 2020). Tam and Ho (2005) show that a higher tailoring level persuades consumers more to accept personalized offers. Moreover, a higher tailoring level allows for trust-building (e.g. Nilashi *et al.*, 2016) and leads to more positive consumer outcomes by reducing information overload and evaluation cost (Liang *et al.*, 2006; Nath and Mckechnie, 2016). Moreover, a tipping point may emerge when consumers feel that firms know too much about them. In these situations, consumers may perceive violations of their privacy (Kubicka, 2016) and intrusion into their lives (Thirumalai and Sinha, 2013). Moreover, these issues may prompt users to distrust firms, especially if they do not recall having given consent to the firm for using their personal information (Aguirre *et al.*, 2015). As such, personalization at a higher level may not always generate the expected return-on-investment (Fan and Poole, 2006), and may cause the reactance behavior in consumers as well because of perceived restriction on freedom of choice (Bleier *et al.*, 2018). As such, the explicit costs of personalization may exceed its value (Montgomery and Smith, 2009).

Tailoring Dynamics reflects the extent to which personalized offers emerge based on in-the-moment or not, and hence strongly links with the timing of learning. *Static tailoring* relates to situations where firms adapt offerings and touchpoints based on historical knowledge of the consumer and hence links to retrospective data collection. Static tailoring assumes that consumers' preferences are rather stable and do not change rapidly. *Adaptive tailoring* corresponds to situations where firms adapt offerings and touchpoints based on real-time collected data and insights (Ho *et al.*, 2011). The difference with the timing of learning resides in the actual usage of data, meaning that, to capture the dynamics of preference change, adaptive tailoring understands consumers' context, infers interests, and adapts the offering based on the most recent preferences as opposed to static tailoring that adapts offering based on consumer's historical preference data. While a big number of articles investigate tailoring dynamics (61.5%, $n = 83$), static tailoring (44.4%) has been the dominant focus compared to dynamic tailoring (9.6%) – see Table 2.

Several studies suggest that adaptive tailoring is perceived as better than static tailoring by consumers because this tailoring style allows adaptation to gradual changes of consumer preferences over time (Chung *et al.*, 2016), yields better consumer experience (Liebman *et al.*, 2019), requires minimal proactive consumer input (Wedel and Kannan, 2016) and typically leads to a better match with consumers' spontaneous preferences (Ho *et al.*, 2011). However, real-time adaptation can also increase perceived intrusiveness of the experience (Smink *et al.*, 2020). Static tailoring poses less severe challenges for a firm to implement and may be preferable in situations where the firm does not have the necessary technical skills in-house to set up an adaptive personalization system (Chung *et al.*, 2009; Glushko and Nomorosa, 2012).

Personalization: future research avenues

From the structured literature review with content analysis, we can discern that personalization initiatives can be anatomized into two key building blocks, each having various components: learning (i.e. manner, transparency, and timing) and tailoring (i.e. touchpoint, level, and dynamics). Any managerial decision in relation to the distinguished learning and tailoring components can essentially encourage or discourage consumers to pursue their journey with the firm and even affect their relationship with the firm. Indeed, each of the learning and tailoring decisions goes along with a dilemma (i.e. between explicit/implicit, overt/covert, real-time/retrospective learning, and digital/human/physical, low/high, and static/adaptive tailoring) where a choice needs to be made from the firm's side.

From this content analysis and given that new technologies and AI are further pushing the expectations around and the application of personalization in consumer-firm encounters, new challenges and opportunities arise. Today, organizations struggle significantly with making their personalization efforts work and pay-off (Dynamic Yield, 2020). This even makes some marketers think about (partly) abandoning their personalization efforts (Gartner, 2019). This is paradoxical given that most managers put personalization high on the agenda (Harvard Business Review Analytic Services, 2018) and the fact that consumers expect it more and more (Accenture, 2018). Against this background, more knowledge is required to aid practice toward the successful implementation of personalization practices. Below, we outline various research opportunities related to the learning and tailoring components – note that some components provide more research opportunities than others. Table 3 provides a summary of the relevant future research avenues. After, we outline several general guidelines to implement the research agenda, largely building on the theoretical, contextual, and methodological data that was coded from the literature set. T3

Research avenues linked to learning components

Manner of Learning – Explicit learning intuitively seems a viable learning strategy but practically, as Murray and Häubl (2009) contend, asking consumers for information may be perceived as too interrogative and may therefore result in loss of consumers' willingness to actually provide information or consumers may provide wrong information to protect their privacy (Glushko and Nomorosa, 2012). Future research could investigate the conditions under which firms can mitigate consumers' reluctance to share their data when explicitly asked for, so that explicit learning creates value for both the consumer and the firm. In this regard, researchers may distinguish various types of data such as identification, demographic, lifestyle, media usage, medical, financial, and location-based data (Bansal *et al.*, 2016) of which some types may be considered more sensitive to consumers (e.g. financial data vs demographic data) than other types (Grosso *et al.*, 2020). Research should also explore ways to limit the burden of time and effort when opting for explicit learning (Glushko and Nomorosa, 2012; Gretzel and Fesenmaier, 2006). In some situations, firms need initial consumer input to kickstart the personalization process. For instance, early in the relationship firms do not have any individual-level data (i.e. cold-start problem), making that input via quizzes is an often used and necessary tool to make personalization efforts work. Here, it is also important to understand what drivers may help to motivate consumers to share data. A recent practitioner report, for instance, shows that consumers' willingness to share their personal data is higher when they can receive exclusive discounts, have problems solved, receive back-in-stock alerts, get personalized recommendations and to find products faster and easier (SmarterHQ, 2019).

Today, there is also a growing tendency to give consumers more control of their personal data and how firms may use this – in part driven by legislation like Europe's GDPR and a growing number of initiatives that work toward decentralized, person-owned and controlled data ownership like Dataswift (https://www.dataswift.io/) and the MIT Solid project (https://solid.mit.edu/). The 2020 Cisco Consumer Privacy Study, for instance, finds 89% of respondents wanting more control of their personal data (Cisco, 2020). More work is needed to

Table 3. Future research directions

Building block	Component	Future research directions
Learning	Manner	• When are consumers willing to share personal data for personalization purposes? How can firms motivate consumers to share their data? • To what extent does providing consumers with control over their data (usage) a competitive advantage for firms? • What tools can be developed to give consumers more control over data collection and usage without overburdening them? • How can implicit learning via third party data be enhanced? • How transparent should implicit learning be? Are there variations across industries? • Under what conditions do consumers prefer explicit vs implicit learning? • What types of data are consumers willing to share? • How can new privacy-preserving mechanisms like Google's FLoC impact firms' attempts of collecting individual level consumer data?
	Transparency	• When do consumers feel a need for transparency? • To what level of detail do consumers want insights on how their personal data is being collected and used? • When does transparency positively/negatively impact consumer/firm outcomes? • To what extent do consumers value getting insight on how their data is being used for personalization? • Have new regulations (e.g. GDPR) enhanced/diminished consumers demand for transparency?
	Timing	• What is the good time to gather and analyze different types of information for personalization? • What is the predictive value for personalization of different data types? • How can real-time learning be used to enhance the consumer journey? What role can new technologies (e.g. conversational agents) play?

(*continued*)

Table 3.

Building block	Component	Future research directions
Tailoring	Touchpoint	• When should touchpoints be personalized? When not? • What type of touchpoint personalization is considered as more intrusive by consumers? • How do personalization preferences differ across different types of touchpoints? How can firms optimize the personalization mix? • How do timing, content and customer heterogeneity impact retargeted ads' effectiveness? • How can firms personalize consecutive journeys consistently over time? • Where along the consumer journey does personalization have the strongest impact on consumers? • How does the use of enhancement technologies to personalize human and physical touchpoints impact consumers? • How will changes in learning like FLoC impact the role and success of touchpoints? • What benefits does targeting consumers at firms' own locations (geo-fencing) and at competitors' locations (geo-conquesting) with personalized advertising yield for firms?
	Level	• What is the impact of personalization gone wrong? • When are lower vs higher levels of personalization desired? What consumer- and firm-related factors are at play? • At what frequency should touchpoints be highly personalized? • Are higher vs lower levels of personalization more (or less) accepted at different touchpoint types? • What techniques/interventions can be made to reduce the odds of raising consumer feelings of intrusion and privacy violation under high tailoring conditions?
	Dynamics	• When do consumer prefer adaptive over static tailoring? • What data enables adaptive tailoring in a reliable manner? • What data is most acceptable for adaptive tailoring purposes? • How do consumers react to firms merging first party and third-party data for personalization purposes? • How do consumers respond to firms' personalization efforts after deprecation of third-party cookies (or cookies at all)?

understand what tools can be developed to give consumers more control over their personal data collection and usage, and to what extent providing consumers with control over their data (usage) provides a competitive advantage for firms.

As evident from Table 2, the case of implicit learning is somewhat under-researched and requires more attention. Implicit learning based on third-party consumer profiling, for instance, is increasingly questioned and considered a "black box" with low reliability and being economically unattractive (Neumann *et al.*, 2019). As such, research is needed to consider how the effectiveness of implicit learning through third party data may be improved. Another interesting angle here is to look at the interplay between implicit learning and learning transparency. For instance, if firms make use of implicit learning (e.g. past purchase history of a consumer that is stored in the firm's database) for personalization purposes, should the firm disclose this practice with its consumers (i.e. overt transparency) or not? While the findings of Grosso *et al.* (2020) show that consumers are indeed concerned about how firms use their data, it is unclear how transparency choices in case of implicit learning affect the success of personalization strategies. Moreover, are there variations across industries? A recent practitioner report (SmarterHQ, 2019) shows that consumers also hold different levels of trust toward distinct firms and industries as to how they use data responsibly – Amazon held the highest score here with 48.3% of respondents claiming to trust the firm with personal data, whereas trust in airlines (17.1%), hotels (14%), boutique stores (7.1%) and social media firms (6.3%) was significantly lower.

Finally, more work is needed to understand when consumers prefer explicit vs implicit learning. For example, consumers having developed a strong and long-lasting relationship with a firm may feel a lower need to explicitly provide input, whereas in the initial relationship stages consumers may have a higher preference for explicit learning. Different data types may also be important here, with consumers being more or less willing to share data for personalization purposes and wanting different levels of control on what is shared and used. Online browsing data, for instance, may be considered as less critical compared to the collection, storage, and usage of one's biometric data. The latter data type is tied to an individual and typically allows to uniquely identify an individual (Jain *et al.*, 2011). Moreover, biometric data further allows to build detailed individual profiles on an emotional (i.e. what is the consumer feeling?), cognitive (i.e. what is the consumer thinking?), physical (i.e. what type of consumer is this?) and behavioral (i.e. what is the consumer doing?) level (De Keyser *et al.*, 2021). Given these higher levels of detail and personal information, consumers may want to control their collection and usage more explicitly.

Transparency of Learning – Despite initial findings showing the positive impact of higher transparency levels on consumer outcomes, Table 2 shows that transparency has received relatively little attention in personalization research. This is surprising given how prominent the topic of transparency is on today's agenda. A report by SmarterHQ (2019), for instance, finds that 86% of consumers are concerned about their data privacy, and 79% of consumers believe firms know too much about them. In addition, the *State of Personalization* report by Segment.io finds trustworthiness and transparency to be the key drivers of brand purchases (Segment.io, 2021). Research is needed to understand to when consumer feel a need for transparency (e.g. in the context of ads or product recommendations), what level of detail consumers want to have insights on how their data is being collected, stored and used, how they want to be informed about this, how strongly they value insight on how data is being used for personalization, and under what circumstances transparency positively/negatively impacts consumer outcomes. Recent work by Kim *et al.* (2019b) shows that transparency in an online ad context may even have a negative effect on ad effectiveness in situations where consumers find an inappropriate flow of information used to personalize communication.

Finally, it would be interesting to consider the impact of transparency-promoting legislation like Europe's GDPR on consumers' need for transparency. Has such legislation increased consumer's need for transparency, or does it in fact diminish in a paradoxical manner this potential need knowing that firms are automatically facing limitations on data collection and usage through this legislation? For instance, what is the impact of just informing consumers vs asking their consent (e.g. in case of overt transparency) on their risk and trust perceptions and their willingness to share data for personalization purposes. Moreover, federated learning of cohorts (FLoC), a new mechanism to preserve the privacy of consumers proposed by Google, disables firms to learn about individual consumers based upon the information that third-party cookies from Google Chrome generated for them (Epasto *et al.*, 2021). Instead, FLoC allows firms to learn about consumer groups (cf. group-level or one-to-N personalization) rather than about individual consumers (cf. individual-level personalization). Against this background, future research can and must investigate the effects of this privacy-preserving mechanism on the effectiveness of personalization efforts for safeguarding consumers' privacy while boosting the firm performance.

Timing of Learning – From the firm's side, it is important to better understand the ideal timing to gather different types of consumer information (i.e. retrospective and/or in real-time), and the way in which data from different sources may be linked to one another over time. The more data (both in terms of the manner of data collection, and the longitudinal aspect linked to a real-time tracking and acting upon data) firms can gather, the better equipped they are in making personalized offerings. Further research is needed to understand the usability and predictive value of different types of data – e.g. transactional, web analytics, biometric and social media – in terms of personalization success for consumers and the firm.

As shown in Table 2, personalization dominantly focused on retrospective learning to date. Future research may generate a better understanding of the effectiveness of technological enhancement in terms of real-time learning – especially as 43% of firms see getting accurate and real-time data as a key challenge to their personalization efforts (Segment.io, 2021). As AI-enabled technologies like conversational agents and service robots now enable firms to learn consumer preferences in real-time by recognizing patterns from data as they step along the consumer journey (Huang and Rust, 2021), novel work may help to generate a better understanding of ways to gather and use real-time information to enhance the consumer experience (De Keyser *et al.*, 2020), and how reliable different data types turn out to be.

Research avenues linked to tailoring components

Tailoring of Touchpoints – Personalization efforts in relation to different – digital, human, physical – touchpoints along the consumer journey offer a fruitful area for further research. Work, for instance, is needed to understand how personalization preferences differ across different touchpoints, and where personalization is more vs less desired. Industry data, for instance, show that consumers are disposed negatively to website pop-ups, push notifications and online retargeting/remarketing (SmarterHQ, 2019). While many of these personalized touchpoints are common and popular in practice today, there are mixed results pertaining to their effectiveness and desirability. Li *et al.* (2021), for instance, find early retargeted ads have negative effects on consumer purchases, whereas late retargeted ads have a positive effect. Industry data show that the click-through rate of retargeted ads is ten times higher than that of a typical display ad (Wishpond, 2022), yet they may also lead some consumers to feel annoyed and react negatively to ads of products they viewed earlier (Ghose and Todri-Adamopoulos, 2016). More research is needed to understand how various touchpoints can be personalized so that consumers' potential negative dispositions are reduced, under what circumstances (e.g. consumers already bought what is suggested) it would be better to stay away from personalization, and what type of touchpoint personalization is considered as less appropriate or more intrusive. In relation to retargeting, more insights are needed as to how their timing, content, and customer heterogeneity impact their effectiveness.

From a longitudinal perspective, future efforts are needed to understand where along the consumer journey personalization has the strongest impact on consumers and how firms can personalize consumer journeys consistently over time – i.e. how can firms personalize the mix of touchpoints across channels, devices, and time to deliver superior consumer experiences? Today, only a minority of businesses are investing successfully in omnichannel personalization, leaving much room for needed improvements and overcoming internal challenges like departmental silos and legacy infrastructure (Segment.io, 2021). One such research area is in the field of personalized advertising. As personalized advertising departs from conventional approaches articulating consumers' own preferences, programmatic advertising and location-based advertising on mobile devices offer huge potential for future research. The initial enthusiasm over programmatic advertising seems to fade away due to limited control of advertisers on websites on which their ads appear and due to recent industry developments, such as Google's announcement to limit the use of third-party cookies which will consequently restrict access to users' browsing data, a prerequisite for individual users targeting in programmatic advertising (Shehu *et al.*, 2021). Research is needed to see how current changes will impact the role and success of programmatic advertising. Location-based advertising equally holds great potential for future development and research. The success of the sharing economy (e.g. ride hailing and ride sharing services), for instance, partly depends on consumer geo-location information (Tong *et al.*, 2020). Applying insights with consumer geo-location information, firms can design geo-targeting strategies (geo-fencing and geo-conquesting strategies) (Tong *et al.*, 2020). The increased popularity of mobile devices in consumer shopping journeys has enabled retailers to convert front traffic, i.e. consumers walking in front of a store, into sales with the help of geo-fencing mobile advertising (Baier and Rese, 2020) and through geo-conquesting strategies, i.e. targeting consumers who are at competitors' location (Dubé *et al.*, 2017). Targeting consumers at firms' own location (geo-fencing) and at competitors' location (geo-conquesting) with personalized advertising can be interesting avenue for future research in the area of personalized advertising.

As shown in Table 2, most research attention has been dedicated to personalization in relation to digital touchpoints. However, many consumer journeys also involve physical and human touchpoints (Hamilton *et al.*, 2020). More work is needed to understand how personalization of human and physical touchpoints impacts consumers. Of particular interest is the use of technology to augment the human and physical frontline through for instance physical profiling and emotion-recognition (Grewal *et al.*, 2020) and the impact it may have on consumers: how does the use of different types of enhancement technologies for personalization impact consumers? To what extent does the (un)awareness of enhancement technologies positively/negatively impact the consumer experience?

Tailoring Level – It is important to understand when personalization should be applied and at what level. The cost of personalization gone wrong is rather high. In a recent practitioner study by Broadridge (2021), for instance, 43% of respondents indicate to have stopped business with a firm because they did a poor job of personalizing the experience – up from 25% in 2019. Hence, it may be that in some situations lower or no tailoring levels are better than high levels that are off. In a related fashion, research by SmarterHQ (2019) shows that consumers feeling targeted too many times or for a too long time are offset by personalization efforts. Together, this leads to a set of highly important research questions: What is the impact of non-fitting personalization efforts? When are lower vs higher levels of personalization desired? At what frequency should touchpoints be highly personalized? And for how long?

Higher levels of personalization may be linked to heightened feelings of intrusiveness and privacy violation (Kubicka, 2016; Thirumalai and Sinha, 2013). Indeed, consumers may prefer low over high tailoring levels when they are not ready to disclose their personal information and/or accept interference into their lives (Henkens *et al.*, 2021). In addition, the place where consumers are confronted with highly personalized offerings may be relevant, such as one's home context (where one enjoys privacy) vs a shopping mall (where others may observe how touchpoints get personalized). In this context, future research might investigate how mitigating consumers to higher tailoring levels affects the success of personalization strategies from a consumer and firm perspective, thereby allowing practitioners to decide whether this is a strategy worth pursuing. In addition, work may also consider what techniques/interventions can be made to reduce the odds of raising consumer feelings of intrusion and privacy violation under high tailoring conditions (Wedel and Kannan, 2016).

Tailoring Dynamics – In relation to tailoring dynamics, more research is needed on the topic of adaptive tailoring – see Table 2. Initial work shows how adaptive tailoring is able to deliver better consumer experiences and firm results in comparison with static tailoring (Chung *et al.*, 2016). More insights are needed to understand under what circumstances consumers prefer adaptive over static tailoring, and how a shift to adaptive tailoring should be disclosed and communicated to consumers.

Considering the challenge of collecting and analyzing real-time consumer data (Segment.io, 2021), another series of questions relates to their reliability for personalization purposes. Biometric systems, for instance, are increasingly used to capture consumer emotions (e.g. Affectiva emotion recognition and Amazon Halo Bracelet) through facial expressions and speech patterns. Research by Barrett *et al.* (2019), however, finds it is very hard to use facial expressions to accurately predict how someone is feeling. These facial expressions can be fake and vary across contexts and cultures, often leading to misinterpretations by the software analyzing. More work is hence needed to uncover what data types are reliable for and enable adaptive tailoring the most, what data types are considered acceptable for personalization purposes, and how consumers react to misinterpretations of data. Relatedly, more insights on consumer reactions to different types of information flows and data-merging practices are needed as firms find significant potential in merging and using a mix of first party (i.e. data collected by the firm) and third-party (i.e. data collected by an outside party) data for personalization purposes. Furthermore, based on the insights drawn during the process of analyzing extant personalization literature, we came across multiple aspects which we think personalization researchers should consider to make personalization research more impactful.

Enhancing the impact of personalization research

Combining the coding of the theories used, study contexts and methodologies used in our set of 184 studies and our overall research synthesis, we outline five considerations researchers should take into account to enhance the impact and practical value of their work: (1) accounting for heterogeneity, (2) embedding theoretical perspectives, (3) infusing methodological innovation, (4) adopting appropriate evaluation metrics, and (5) dealing with legal/ethical challenges. In what follows, we turn these five considerations into concrete recommendations to ensure impactful personalization research.

Accounting for heterogeneity

The inherent differences between consumers and contexts warrant a further investigation of heterogeneity in personalization research. Specifically, researchers may want to account for consumer-related (e.g. culture), personalization object-related (e.g. email, product and advertising), and industry-related (e.g. industry type) heterogeneity.

T4 From Table 4, we can see that personalization literature to date has mainly used samples from Western, educated, industrialized, rich and democratic (WEIRD) countries, especially from the United States (22.28%). Research in African and Latin-American settings is virtually lacking. Asian countries, in turn, are underrepresented, which is highly surprising given the strong digital push countries like China are making through firms like Alibaba and Tencent. These data-rich and developing market environments (Sridhar and Fang, 2019) provide significant opportunities for personalization research and should be strongly considered in future endeavors. In addition, as more firms are operating globally and as societies are becoming more ethnically diverse within countries as well, this leaves firms simultaneously facing consumers with different cultural backgrounds. Cross-cultural personalization research could assist managers in understanding cross-cultural variation at an individual consumer level and help adapt personalization efforts accordingly.

T5 Moreover, as shown in Table 5, the object of personalization in research is dominantly related to promotion, with different types of ads (28.80% of studies – e.g. Tran *et al.*, 2021; Van Den Broeck *et al.*, 2020) and product/service recommendations (19.57% of studies – e.g. Kang and Namkung, 2019) as the two biggest categories of objects. Personalization of other aspects of the marketing mix also deserves further investigation, such as personalized pricing (Tong *et al.*, 2020) and personalized interactions with the firm's representatives in the physical – as opposed to the digital – reality (De Keyser *et al.*, 2019). Here, many opportunities lie in considering how personalization of human frontline interactions, physical/digital encounters through adaptive augment/virtual reality, and conversational agents and robots impact consumer and firm outcomes.

Country	# of studies (%) (n = 184)*
The USA	41 (22.28%)
Multi-country	10 (5.43%)
Germany	9 (4.89%)
Korea	8 (4.35%)
Belgium	7 (3.80%)
The Netherlands	7 (3.80%)
Hong Kong	5 (2.72%)
China	5 (2.72%)
Greece	3 (1.63%)
Switzerland	2 (1.09%)
Taiwan	2 (1.09%)
Canada	2 (1.09%)
Japan	2 (1.09%)
Portugal	1 (0.54%)
The UK	1 (0.54%)
Cyprus	1 (0.54%)
Ireland	1 (0.54%)
Bolivia	1 (0.54%)
Turkey	1 (0.54%)
Italy	1 (0.54%)
New Zealand	1 (0.54%)
Malaysia	1 (0.54%)
Finland	1 (0.54%)
Palestine	1 (0.54%)
N/A	20 (10.87%)
Not specified	50 (27.17%)

Note(s): *While we systematically reviewed 135 articles, the numbers in this table refer to studies within these articles. That is, a single article may contain more than one study

Table 4. Country focus in personalization research

Object	# of studies (%) (n = 184)*
Ads (web, banner, email, mobile)	53 (28.80%)
Recommendations (product, service, events)	36 (19.57%)
Service/service encounter	22 (11.96%)
Website (info, content, interface, pages)	21 (11.41%)
Email	12 (6.52%)
News/newsletter	5 (2.72%)
Mail survey	2 (1.09%)
Others	16 (8.70%)
Not specified	5 (2.72%)
N/A	12 (6.52%)

Note(s): *While we systematically reviewed 135 articles, the numbers in this table refer to studies within these articles. That is, a single article may contain more than one study

Table 5. Objects personalized in personalization research

Finally, personalization research should account for industry-specific effects. To date, especially (online) retailers have made great strides to personalize the consumer experience (IBM, 2020), with academic research focusing dominantly on this setting (27.17% – see Table 6). Novel personalization research should consider expanding the scope of settings, with financial services, healthcare, and education providing particularly interesting settings to consider the impact of personalization on consumer and firm outcomes and – given the social importance of some of these sectors – even societal outcomes. T6

Embedding theoretical perspectives

Looking at the coded theories, it becomes clear that most of the personalization articles to date are not building on a concrete theoretical basis (see Table 7 – 69.63% of articles do not have a clear guiding theory). Other articles borrow insights from or contribute to a wide variety of theoretical perspectives that serve as a starting point for more impactful personalization research. T7

First, the different theories listed in Table 7 suggest that personalization efforts can elicit specific behaviors through mental processes (e.g. theory of reasoned action, theory of planned behavior, stimulus-organism-response model, uses and gratification theory, elaboration likelihood model, and tripartite model of attitude formation). These mental processes entail,

Contexts	# of studies (%) (n = 184)*
Online retail(ers)	50 (27.17%)
Hospitality	12 (6.52%)
News media	9 (4.89%)
Bank	9 (4.89%)
Entertainment	9 (4.89%)
Social media (ads)	9 (4.89%)
Telecom	8 (4.35%)
Travel	6 (3.26%)
Healthcare	5 (2.72%)
Automotive	4 (2.17%)
Other	44 (23.91%)
N/A	19 (10.33%)

Note(s): *While we systematically reviewed 135 articles, the numbers in this table refer to studies within these articles. That is, a single article may contain more than one study

Table 6. Settings used in personalization research

Theory	No. of articles	%
Elaboration likelihood model (ELM)	4	2.96
Consumer search theory (CST)	3	2.22
Uses and gratification theory	3	2.22
Theory of reasoned action (TRA)	3	2.22
Complexity theory	2	1.48
Information boundary theory	2	1.48
Privacy calculus theory	2	1.48
Psychological reactance theory	2	1.48
Self-concept theory	2	1.48
Stimulus-organism-response (S-O-R) model	2	1.48
Configuration theory	1	0.74
Utility maximization framework	1	0.74
Expectation confirmation theory	1	0.74
Social identity approach	1	0.74
Technology acceptance model (TAM)	1	0.74
Theory of planned behavior	1	0.74
Transaction cost theory	1	0.74
Perceived care theory	1	0.74
Uniqueness theory	1	0.74
Principle of least effort	1	0.74
Information overload theory	1	0.74
User involvement theory	1	0.74
Play and entertainment theories	1	0.74
Tripartite model of attitude formation	1	0.74
Information processing theory	1	0.74
Innovation diffusion theory (IDT)	1	0.74
Culture–Technology fit theory	1	0.74
Theory of constructed preferences	1	0.74
Social cognitive theory	1	0.74
Social-interaction theory	1	0.74
Knowledge-based trust theory	1	0.74
Cognitive control theory	1	0.74
Attribution theory	1	0.74
Ideal type theory	1	0.74
SERVQUAL	1	0.74
SERVPERF	1	0.74
Social presence theory	1	0.74
Communication privacy management (CPM) theory	1	0.74
Regulatory focus theory	1	0.74
Ego-depletion theory	1	0.74
Multiple resource theory	1	0.74
Social contract theory	1	0.74
Privacy paradox	1	0.74
Impression management theory	1	0.74
Cue utilization theory	1	0.74
Evolution theory	1	0.74
Motivation theory	1	0.74
No guiding theory	94	69.63

Note(s): As one article may build on multiple theoretical perspectives, the number of articles amount to more than 135 articles. We use 135 articles as the basis to calculate the relative frequencies

Table 7. Theories employed in personalization research

among others, emotional responses, gratification, attitude formation, perceptions, subjective norms, and intentions. Additionally, extant research also theorizes about how and why personalization efforts affect these mental processes, thereby paying attention to information processing (e.g. information overload theory, information boundary theory, cue utilization theory, ideal type theory, multiple resource theory and cognitive control theory), decision-making (e.g. utility maximalization framework, communication privacy management theory, privacy calculus theory, and privacy paradox), and motivational processes (cf. motivation theory, transaction cost theory, perceived care theory, psychological reactance theory, and regulatory focus theory). An integration of the aforementioned theoretical perspectives may contribute to a better understanding of the mental processes through which personalization efforts with unique combinations of learning and tailoring components elicit specific consumer behaviors like disclosing personal data and continued usage of personalized offerings.

In this regard, it is important to consider mental processes that are cognitive (e.g. expectation (dis)confirmation through perceptions) as well as affective (e.g. gratification after using personalized offerings) in nature. Over the years, cognitive processes received much more thought than emotional processes in the personalization literature. Indeed, the dominant method for gathering data about these processes – that is, surveys – is more likely to capture cognitive rather than emotional processes as surveys urge respondents to reflect upon their answers. As such, methodological innovations like neuroscientific tools will have to be implemented to capture the multidimensional nature of mental processes triggered by personalization efforts.

Another interesting avenue for future research from a theoretical perspective relates to the way in which personalization efforts contribute to consumer's identity formation and impression management. Recent personalization research suggests that identity-related theories like social identity theory, uniqueness theory, and self-concept theory (e.g. Torrico and Frank, 2017; Tran *et al.*, 2020a) and impression management theory (e.g. Hess *et al.*, 2020) are applicable in the context of personalization. Moreover, personalization researchers can enrich these theories by discovering new triggers for identity formation and impression management when investigating the role of different learning and tailoring components. In data-rich environments, future research may also benefit from investigating whether digital identities evolve along parallel lines with those in the physical reality and – if not – how and why they differ from one another along with its implications for the effectiveness of personalization efforts. Inspired by social presence theory, future research might also investigate to what extent consumers are perceived as "real persons" when brands and firms rely upon their digital identities and how this informs their learning and tailoring decisions and subsequently affects the effectiveness of these decisions.

Infusing methodological innovation

The empirical studies in our structured literature review dominantly rely on scenario-based experiments (lab experiments – 16.85%; online experiments – 19.57%) and retrospective surveys (e.g. online surveys – 13.59%) – see Table 8. While both methods have their merits, T8
experiments may not capture the complexity and richness of reality (Tojib and Khajehzadeh, 2014) and surveys suffer from a variety of biases (Verhulst *et al.*, 2019). Hence, personalization researchers need to embrace a wider set of methodologies to strengthen insights generated.

First, while efforts focused on, among others, optimizing recommendation algorithms is highly advanced in nature and making use of machine leaning techniques, academic work on the consumer/firm outcomes of personalization initiatives is less advanced to date. In this regard, personalization research would benefit from more advanced data and analytical techniques for quantitative approaches. Specifically, conjoint analysis could assist in finding optimal combinations of learning and tailoring choices for consumers and firms. Churn and hazard modeling, in turn, could help to demonstrate the power of personalization efforts, for instance as reflected in the financial impact of personalizing consumer experiences.

Method	# of studies (%) (n = 184)*
Conceptual	13 (7.07%)
Experiment	104 (56.52%)
Lab experiment	31 (16.85%)
Online experiment	36 (19.57%)
Field experiment	24 (13.04%)
Experiment (not specified)	13 (7.07%)
Survey	39 (21.20%)
Field survey	4 (2.17%)
Online survey	25 (13.59%)
Mail survey	7 (3.80%)
Survey (not specified)	3 (1.63%)
Website content/data analysis	8 (4.35%)
Interview	6 (3.26%)
Literature review	6 (3.26%)
Case study	2 (1.09%)
Fuzzy set qualitative comparative analysis (fsQCA)	2 (1.09%)
Text mining	1 (0.54%)
Simulation	1 (0.54%)
Critical incident techniques	1 (0.54%)
fMRI (neural experiment)	1 (0.54%)

Note(s): *While we systematically reviewed 135 articles, the numbers in this table refer to studies within these articles. That is, a single article may contain more than one study

Table 8. Empirical methods in personalization research

Neuroscientific tools like EEG, fMRI, and eye tracking (Verhulst *et al.*, 2019) could assist in uncovering cognitive and affective processes linked to different personalization decisions. In addition, modeling approaches like multilevel analysis and random effects models allow to go beyond population-averaged findings.

At the same time, the adoption of qualitative work – which is largely missing at this point – may bring more depth to personalization research. Specifically, case study research may be beneficial to provide insights into why some personalization initiatives are highly successful while others fail. By means of qualitative (comparative) analyses of these personalization cases, future research may contribute to a better understanding of the way in which learning and tailoring decisions affect the success of a personalization initiative. As a matter of fact, researchers may find the work of Neuhofer *et al.* (2015), Pappas (2018), Pappas *et al.* (2016), and Piccoli *et al.* (2017) insightful, as these studies already conduct case study research and fuzzy-set qualitative comparative analyses (fsQCA) in the field of personalization. Yet, none of these studies considers the way in which learning and tailoring decisions affect personalization success. In addition, phenomenological research may aid to gain insight into the "lived" personalization initiatives, i.e. how consumers experience specific personalization decisions made by a firm (e.g. Apple's decision to reverse default settings of its operating system so that apps can only track Internet behavior if consumers explicitly approve it).

Adopting appropriate evaluation metrics

To explore the implications of personalization efforts, most studies rely upon consumer metrics that are perceptual in nature such as purchase/continuance intentions, click-through intentions, satisfaction, trust, attitude toward the firm, and other behavioral
T9 intentions – see Table 9. To strengthen the impact on practice, personalization researchers should strive to enhance the usage of hard consumer metrics such as churn, retention, basket size, purchase frequency, and lifetime value that connect to actual consumer

Outcomes	No. of studies	%
Consumer intentions	83	40.10%
Purchase/continuance intentions	56	27.05%
Click-through intentions	17	8.21%
Word-of-mouth intentions	7	3.38%
Intentions to disclose information	3	1.45%
Consumer behaviors	38	18.36%
Acceptance of personalization	7	3.38%
Resistance to personalization	6	2.90%
Other behaviors (e.g. click-through, rating behavior, . . .)	25	12.08%
Consumer attitudes	14	6.76%
Consumer satisfaction	14	6.76%
Service/product quality	13	6.28%
Trust	6	2.90%
Perceived privacy risk	4	1.93%
Other	35	16.91%

Note(s): This table is based on the empirical studies included in the dataset. One study may incorporate multiple outcomes, resulting in 207 outcomes

Table 9. Evaluation metrics employed in personalization research

behaviors. Moreover, the connection of consumer metrics with financial metrics at the firm level is necessary to (dis)confirm the effectiveness of personalization efforts to boost the financial performance. Initial practitioner research seems to suggest a positive connection between personalization and firm financials. Specifically, a white paper by Forrester Consulting (2020) reports successful personalization to lead to an average of 5.63% increase in sales revenue, a 4.64% in consumers won, a 2.81% rise in consumer retention rates, and a 2.57% improvement in average order value. If academic research can confirm this return-on-personalization along with its boundary conditions (cf. the consumer-related, industry-related, and personalization object-related heterogeneity discussed above, along with its methodological underpinnings), this may further support firms in expanding their personalization efforts. In connection, research is also needed to aid in discerning "relevant" from "non-relevant" personalization efforts. For online (retargeted) ads, for instance, annual losses to digital ad fraud range from $6.5 billion to $19 billion (Benes, 2019). As such, industry is in high need of methods and metrics that help discern relevant from wasted personalization efforts and investments.

Next to a focus on financial metrics, personalization research may also expand to incorporate a focus on consumer and societal well-being in general. To date, a limited set of research papers like Fan and Poole (2006 – psychological and social welfare) and Lee *et al.* (2011 – personal and social welfare) incorporate some well-being aspect. As personalization is a rapidly growing business practice that is impacting consumers globally, its impact on a broader set of individually and socially relevant outcomes related to well-being and sustainability is critical (Ostrom *et al.*, 2021). Personalization researcher should thus strongly consider expanding their set of measured outcomes beyond the typical perceptual metrics employed in marketing research.

Dealing with legal/ethical challenges

Legal frameworks like Europe's GDPR, Brazil's *Lei Geral de Proteçao de Dados* (LGPD), the California Consumer Privacy Act (CCPA), South Korea's Personal Information Protection Act, and India's Personal Data Protection Bill may limit and regulate the collection and/or use of consumer data. Since many personalization initiatives are driven by and based on individual-level consumer data, these legislations may thus significantly affect a firm's ambitions and success regarding personalized offerings. Several firms – such as Google – are already anticipating for these legislative changes with FLoC as a privacy-preserving mechanism and hence contribute to the deprecation of third-party cookies. Thomaz *et al.* (2020) contend that, in next five to ten years, firms will lose much of their ability to fuel modern marketing practices that heavily rely on abundant, rich, and timely consumer data because of privacy focus of consumers as well as governments. This calls for urgent researchers' attention to develop an understanding of how organization would be able to learn about consumer preferences as a result of different legal bindings in different regions of the world, and how this will impact consumer and firm outcomes accordingly.

Given legal discrepancies, researchers will also need to consider how policy differences across geographical regions (e.g. Asian countries vs USA states vs Europe) affect firms operating globally, how this influences personalization strategies and whether different regions will be confronted with different learning and tailoring practices. As more consumers buy globally today, perceived regulations one's home-country may also warry-over, and affect how they perceive, prefer and deal with personalization practices from firms outside their home-country. Researchers will thus need to consider any such differences caused by governmental interference.

Implications for practice

This personalization review provides practitioners with a new lens to evaluate their take on personalization. Specifically, managers may use our synthesis to assess what they are currently doing in relation to the different personalization building blocks and components, assess how these go together and evaluate whether improvements are possible to enhance the success of personalization activities. It may also lead to careful reflections in relation to personalization – e.g. is our current manner of learning fitting with our current consumer base? What touchpoints could be personalized additionally?

Second, the recognition of personalization entailing various components pushes firms to think about the interaction between the various components. We refrain from putting forth "winning combinations" of the personalization components as these are dependent upon the context (e.g. legal restrictions such as Europe's GDPR) and firm characteristics (e.g. in-house technological skills). From current trends, however, it is clear is that firms need to invest more strongly to deliver in-the-moment personalized interactions, while accounting for concerns about data misusage and an increasingly challenging legal environment limiting data usage.

Third, at no point should firms lose track of how their consumer base is open to personalization, and whether a segmented approach may be needed to address varying levels of looked-after personalization – highly personalized touchpoint may not always be desired, needed and/or (financially) effective. Additionally, firms need to take consumers' desire for transparency and privacy into consideration when implementing the different building blocks of a personalization strategy, for instance by opting for explicit vs implicit learning. Our synthesis may help firms to streamline their strategies for personalized offerings with the various conditions that lead to desired (behavioral) outcomes.

Concluding notes

While personalization research has been around for 50 years, the topic has surged in the last two years in conjunction with the novel possibilities AI is offering. To consolidate, structure and advance our knowledge, this article sought to deliver 3 contributions. First, we systematically reviewed 135 personalization studies and uncovered six personalization components that can be linked to two personalization building blocks: (1) learning: *manner,* *transparency,* and *timing* and (2) tailoring: *touchpoints*, *level*, and *dynamics*. Specifically, these building blocks and their components help researchers and managers to better understand and manage personalization which is a necessary condition to move this field forward. Second, for each of these components, various future research directions were put forth to stimulate further work. Finally, a set of considerations – accounting for heterogeneity, methodological innovation, theoretical embeddedness, adopting financial and well-being metrics, and preparing for legal challenges – was made on how to enhance the impact of novel personalization research on academia and practice. We hope that our efforts to shape thinking about personalization will help to strengthen this highly important area of research and business practice. Moving forward and given that practitioners increasingly adopt a nuanced view on personalization, it will be important to understand under what circumstances personalization is a good business strategy and when it is not. AQ: 7

Note

1. The technical aspects underlying the day-to-day implementation of personalization extend beyond the scope of this study, as other review studies exist in this area (e.g. Park *et al.* (2012) for an excellent literature review on recommender systems and their underlying data mining techniques).

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Further reading AQ: 12

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Appendix

The Appendices for this article can be found online.

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