



**TAKING THE FIRST STEP ON THE
CONSUMER PRIVACY JOURNEY**
THREE ESSAYS ON CONSUMERS' PRIVACY-RELATED
DECISION-MAKING

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“In every job that must be done, there is an element of fun.

You find the fun and snap! The job's a game.”

(Mary Poppins, 1964)

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Summary

Data has become a necessary resource for firm operations in the modern digital world, explaining their growing data gathering efforts. Due to this development, consumers are confronted with decisions to disclose personal data on a daily basis, and have become increasingly intentional about data sharing. While this reluctance to disclose personal data poses challenges for firms, at the same time, it also creates new opportunities for improving privacy-related interactions with customers. This dissertation advocates for a more holistic perspective on consumers' privacy-related decision-making and introduces the consumer privacy journey consisting of three subsequent phases: pre data disclosure, data disclosure, post data disclosure. In three independent essays, I stress the importance of investigating data requests (i.e., the first step of this journey) as they represent a largely neglected, yet, potentially powerful means to influence consumers' decision-making and decision-evaluation processes. Based on dual-processing models of decision-making, this dissertation focuses on both consumers' cognitive and affective evaluations of privacy-related information: First, Essay 1 offers novel conceptualizations and operationalizations of consumers' perceived behavioral control over personal data (i.e., cognitive processing) in the context of Artificial Intelligence (AI)-based data disclosure processes. Next, Essay 2 examines consumers' cognitive and affective processing of a data request that entails relevance arguments as well as relevance-illustrating game elements. Finally, Essay 3 categorizes affective cues that trigger consumers' affective processing of a data request and proposes that such cues need to fit with a specific data disclosure situation to foster long-term decision satisfaction. Collectively, my findings provide research and practice with new insights into consumers' privacy perceptions and behaviors, which are particularly valuable in the context of complex, new (technology-enabled) data disclosure situations.

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1. Introduction

1.1 The Role of Data Requests in the Consumer Privacy Journey

The economy of the 21st century heavily relies on consumer data to thrive. Firms face the pressure to process ever-growing amounts of consumer data to keep up with their competitors and provide their customers with personalized offers and experiences (Bradlow et al., 2017; Martin et al., 2020). To cope with this challenge, they increasingly gather (overtly or covertly) huge amounts of consumer data at different touchpoints along the customer (retail) journey consisting of the pre purchase, purchase, and post purchase phase (Cui et al., 2021; Quach et al., 2022; Steinhoff & Martin, 2022). While practice and academia alike contend that firms' data proliferation efforts increase marketing returns (Martin et al., 2017; Schumann et al., 2014), however, consumers have long been expressing negative attitudes toward data disclosure (e.g., Culnan & Armstrong, 1999): A recent survey indicates that six out of ten Americans believe that it is not possible to go through the day without having their data collected by firms, and express that this creates personal risks (Pew Research Center, 2019). These concerns are fueled by the rise of increasingly sophisticated technological advancements in the context of, for instance, data analytics, Artificial Intelligence (AI), and digital marketing. Besides consumer concerns, changes in regulation further impede firms' data gathering and handling possibilities (Marketing Science Institute, 2022). Thus, firms confront the critical tensions of thoughtfully balancing their customers' needs and complying with regulatory requirements when gathering and exploiting personal data for strengthening their competitive advantage.

Managing these tensions arising from different stakeholder needs requires effort, but addressing them also presents an opportunity for firms to become more thoughtful and consumer-centric in their privacy interactions with their customers.

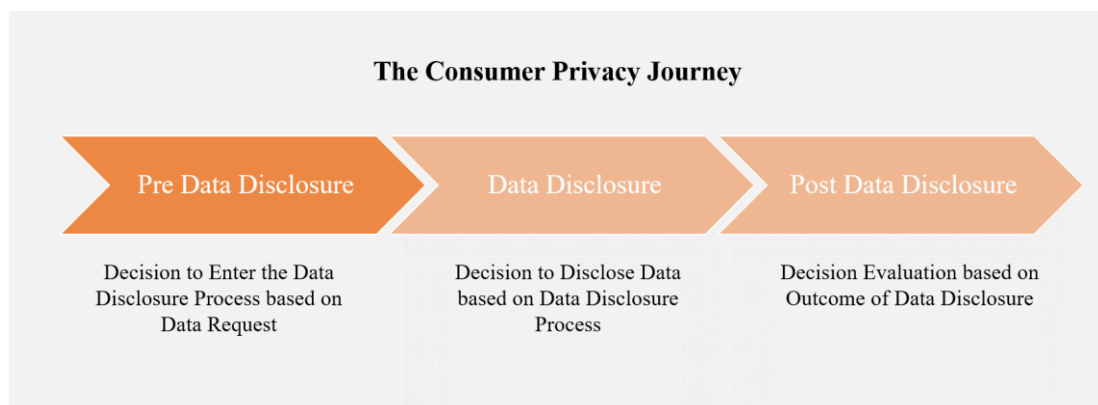
To do so, they need to develop an in-depth understanding of consumers' evaluations of their data disclosure touchpoints, including their reactions when confronted with decisions to enter data disclosure processes, their perceptions as they carry out these processes, and their evaluations of the situations after they have engaged in data disclosure behaviors. To date, however, privacy literature does not offer this holistic perspective of consumer perceptions and behaviors in the context of specific data disclosure touchpoints. Instead, it considers privacy-related touchpoints as one of many touchpoints that consumers face when interacting with a firm (i.e., along the customer (retail) journey; e.g., Aiello et al., 2020; Cui et al., 2021; Martin & Palmatier, 2020); moreover, prior research mainly focuses on consumers' data disclosure behaviors, leaving out what happens before and after the decision to share personal data.

In this dissertation, I adopt a customer journey perspective and propose to treat each specific privacy-related touchpoint as a consumer journey itself to holistically capture consumers' privacy experiences. Specifically, informed by first evidence on the importance of considering interconnected data disclosure decisions (Adjerid et al., 2018), I argue that a consumer's decision to enter a data disclosure process based on the evaluation of a data request (i.e., an inquiry or invitation to disclose personal data) and the decision to actually disclose personal data (i.e., based on a data disclosure process) are conceptually distinct decisions. Furthermore, I suggest that privacy researchers and managers also need to take consumers' decision evaluation after data disclosure into account.

Based on this reasoning, I conceptualize the "*Consumer Privacy Journey*" as consisting of three phases: pre data disclosure, data disclosure, and post data disclosure (see Figure 1.1). Preceding the actual data disclosure decision, consumers are faced with the decision to enter a data disclosure process, that is, with the pre

data disclosure phase. Consumers' evaluation of a presented data request drives their decision to engage with a firm's data disclosure touchpoint. After this initial decision, the data disclosure phase entails consumers' decision to disclose personal data by actively performing a data disclosure process or by having personal data disclosed automatically (i.e., depending on the type of data disclosure; Krafft et al., 2021). For example, after deciding to create a customer profile based on the evaluation of a data request, consumers fill out a contact form with their personal data such as name and address, and submit it to the firm to receive a specific outcome (e.g., personalization or monetary benefit; Hui et al.; Xu et al., 2009). In the post-data disclosure phase, consumers evaluate their data disclosure decision. This evaluation may occur, for instance, after receiving the outcome of data disclosure or learning about the data recipient's (positive or negative) data handling practices (e.g., Martin et al., 2017); consumers' (dis)satisfaction with a data disclosure decision may then bias subsequent decisions to interact with a firm.

Figure 1.1. *The Consumer Privacy Journey.*



As illustrated, consumers' privacy journeys begin with a firm's request to disclose personal data. According to prior research, this first step represents both a critical hurdle and an important opportunity for firms to initiate privacy-related interactions with their customers: it has been shown that if firms manage to convince consumers to enter a data disclosure process, the likelihood that they will actually

disclose personal data increases (Joinson et al., 2007; Schumann et al., 2014).

Therefore, data requests can be viewed as meaningful tools to positively influence consumers' privacy journeys if they are designed in an intentional, consumer-centric way that, for instance, allows consumers to understand the consequences of their decision to engage with a data disclosure touchpoint (i.e., by anticipating the data disclosure process and/ or the outcome of data disclosure).

Despite the importance of data requests in the consumer privacy journey, to date, research has largely neglected to explicitly examine their effectiveness in encouraging consumers to enter a data disclosure process. This gap is surprising, given that, for instance, privacy notices (e.g., cookie tracking requests) often cover more than half of firms' landing pages and are thus likely to shape not only consumers' privacy perceptions and behaviors, but also their overall impressions of firms' websites.

To fill this void, I adopt a dual-processing perspective and focus on understanding consumers' affective and cognitive processing of information when confronted with a data request (Epstein, 1994; Evans & Stanovich, 2013; Finucane et al., 2000; Shiv & Fedorikhin, 1999). In the context of privacy, consumers' cognitive processing based cognitive cues provided in data disclosure situations has already gained considerable research attention (e.g., literature on privacy calculus and privacy concerns; Bleier et al., 2020; Dinev & Hart, 2006; Smith et al., 2011). Yet, further research is needed to understand the nuances of consumers' cognitive evaluations of new (technology-enabled) touchpoints, which likely deviate from traditional data disclosure situations that have been previously studied. Based on research in the context of dual-processing models of decision-making (Epstein, 1994; Evans & Stanovich, 2013; Finucane et al., 2000; Shiv & Fedorikhin, 1999), I further highlight the need to more deeply understand consumers' affective processing of

information when confronted with a privacy-related touchpoint. This is in line with a growing stream of privacy literature investigating affective cues as triggers of affective consumer reactions (Dinev et al., 2015; Gerlach et al., 2019; Kehr et al., 2015; Li et al., 2011). Such affective cues represent means to facilitate privacy-related decision-making by making information more accessible, which is especially important in the modern, complex digital landscape. However, research still lacks an understanding of how affective cues can be employed in data requests a) to motivate consumers' privacy-related decision-making effectively (e.g., when working in conjunction with cognitive cues) and b) to achieve long-term satisfaction with data disclosure decisions.

In sum, I argue that making an effort to understand and to proactively design privacy-related touchpoints (e.g., by using data requests that address consumers' affective and cognitive processing of information in a meaningful manner), firms can leverage their potential and better integrate them along their customer (retail) journeys. As such, this perspective complements prior privacy research that explores how privacy unfolds and needs to be reconciled throughout customer-firm interactions and across customer (retail) journeys (e.g., Aiello et al., 2020; Cui et al., 2021; Martin & Palmatier, 2020). Treating consumer privacy as a "core" (as opposed to a "side") aspect of customer-firm interactions and moving beyond the use of data requests solely as a means of complying with privacy regulation helps to resolve the tensions arising from the growing abundance and complexity of modern data disclosure situations. Against this background, I seek to answer the following overarching research question in three independent essays:

How can data requests be designed to positively influence the consumer privacy journey?

1.2 Research Objectives and Scope

Across three independent essays, I address my overarching research question by seeking a better understanding of how cognitive and affective processing of information (i.e., triggered by cognitive and affective cues) of a data request influence consumers' privacy-related decision-making, that is, the decision to enter a data disclosure process and the decision to disclose personal data, as well as their decision evaluations. Essays 1 and 2 connect the first two stages of the consumer privacy journey. Essay 3 provides a theoretical framework discussing the potential effects of a data request's affective design on consumers' post data disclosure decision evaluations.

In Essay 1, I provide a multistage perspective on consumers' perceived behavioral control over personal data representing a cognitive processing mechanism, including precise definitions and operationalizations. Further, I investigate how consumers' control expectations when confronted with a data request affect their intentions to enter a traditional non-automated (Krafft et al., 2021) vs. AI-based data disclosure process. Next, Essay 2 sheds light on both consumers' cognitive and affective processing of information. My coauthors and I investigate how consumers evaluate data requests previewing data disclosure processes that entail relevance arguments (i.e., cognitive cues) as well as relevance-illustrating game elements (i.e., affective cues).

Finally, Essay 3 categorizes different types of affective cues (i.e., benefit-related, environmental, and social) which can be used to motivate consumers' affective processing of a data request. Based on prior literature, I discuss the importance of creating a fit between the affective cues employed in data requests and the specific data disclosure situation for achieving long-term consumer satisfaction with a disclosure decision.

1.2.1 Essay 1: New Technologies, New Tools, New Tensions: Deriving a Multistage Conceptualization of Consumers' Perceived Data Control in AI-Based Data Disclosure Processes

Essay 1 constitutes a deep dive into consumers' control perceptions (i.e., cognitive processing of information) when confronted with a data request. Both research and practice know about consumers' need for control and have put considerable effort into explicitly designing data requests and processes to evoke high control perceptions (e.g., with privacy assurances; Gerlach et al., 2019; Xu et al., 2008). To date, however, we lack an in-depth understanding of consumers' perceptions of behavioral control over personal data as they unfold across time and related to different data activities (i.e., collection, submission, access, and use). This understanding is needed against the background of evolving technological advancements creating new forms of data disclosure touchpoints (e.g., AI-based data disclosure; de Bellis & Johar, 2020; Puntoni et al., 2021; Quach et al., 2022). Based on a novel, multistage account of perceived behavioral control over personal data across consumer–firm data exchanges, my coauthors and I investigate consumers' specific control perceptions when confronted with new data disclosure settings and processes. Further, we aim to understand the contrast between consumers' perceived loss of control in new AI-based disclosure settings as it relates to perceived process effort and personalization benefits. Thus, this Essay seeks to answer the following research questions:

How do consumers evaluate their specific control perceptions across traditional and novel data disclosure settings and processes, including those powered by AI?

How do consumers' perceptions of control and benefits influence their decision to enter an AI-based (vs. non-automated) data disclosure process?

1.2.2 Essay 2: Increasing Consumers' Willingness to Engage in Data Disclosure Processes through Relevance-Illustrating Game Elements

Moving beyond Essay 1's focus on consumers' rational evaluations of data requests, Essay 2 combines approaches of addressing both consumers' cognitive processing (i.e., meaningful engagement) as well as their affective processing of information (i.e., hedonic engagement; Suh et al., 2017). My coauthors and I integrate research from privacy and gamification literature (Koivisto & Hamari, 2019; Smith et al., 2011) to investigate the effectiveness of augmenting textual relevance arguments (i.e., cognitive cues) with relevance-illustrating game elements (i.e., affective cues) for motivating consumer' data disclosure intentions. We focus on previewing a gamified data disclosure process (i.e., the second phase of the consumer privacy journey) in a data request, and assume that this preview involving affective cues supports the relevance of data disclosure (i.e., cognitive arguments). In doing so, we aim to understand whether this combination of cues increases consumers' meaningful and hedonic engagement when confronted with the decision to enter a data disclosure process. Finally, we investigate how game elements need to be designed to effectively convey the relevance of disclosing personal data (e.g., future benefits; Berger et al., 2018; Eisingerich et al., 2019; Liu et al., 2017; Müller-Stewens et al., 2017) and under which circumstances tailoring game elements to support relevance arguments is particularly important. In Essay 2, we aim to answer the following research question:

Are consumers more likely to comply with a data request if textual relevance arguments are augmented with relevance-illustrating game elements previewing a data disclosure process?

1.2.3 Essay 3: “Trick or Treat!?” – A Situation-Fit-Perspective on Affect in Consumer Privacy

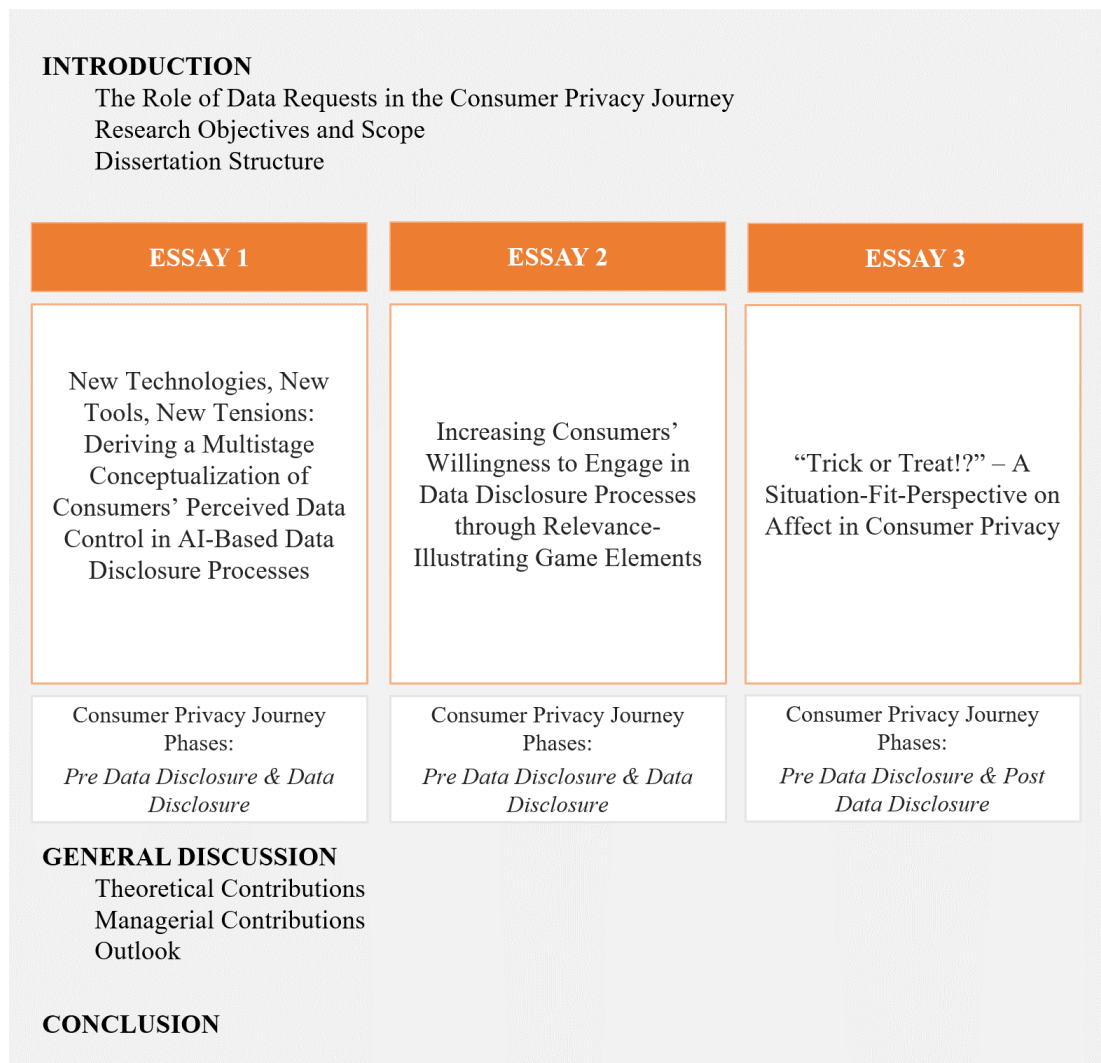
Picking up on Essay 2 focusing on relevance-illustrating game elements as means to motivate consumers’ entering decisions, Essay 3 focuses on different types of affective cues and deals with the question of how their design might influence consumers’ post data disclosure decision evaluations (i.e., third phase of the consumer privacy journey). To do so, this essay categorizes affective cues that have been investigated in prior research (i.e., benefit-related, environmental, and social cues) for a better understanding of how these cues can be implemented by firms to trigger consumers’ affective processing (e.g., Aiello et al., 2020; Gerlach et al., 2019; Kehrer et al., 2015; Li et al., 2017). Adopting a Confirmation-Disconfirmation (C/D) paradigm perspective explaining consumers’ evaluations of a decision (Churchill & Surprenant, 1982; Oliver, 1980; Oliver & DeSarbo, 1988), I introduce a situation-fit perspective on affective cues and argue that it is important to align them to the specific data disclosure decision. Based on this perspective and examples from research and practice, I discuss the potential long-term effects of employing (un)aligned affective cues and derive propositions for each category of affective cues as well as for their interactive effects. The research question driving Essay 3 is:

How do affective cues (i.e., benefit-related, environmental, and social) used in data requests influence consumers’ post data disclosure decision evaluation?

1.3 Dissertation Structure

The remainder of my dissertation is as follows. Chapter 2 comprises Essay 1 which deals with consumers’ cognitive evaluation of a data request by providing comprehensive conceptualizations and measures of consumers’ control perceptions. Chapter 3 introduces Essay 2 examining consumers’ cognitive *and* affective reactions when confronted with data requests featuring relevance arguments (i.e.,

cognitive cues) and relevance-illustrating game elements (i.e., affective cues). Both essays deal with consumers' anticipation of data disclosure processes in data requests (i.e., connecting phases 1 and 2 of the consumer privacy journey). Chapter 4 focuses on the importance of addressing consumers' affective processing when confronted with a data request (Essay 3). I provide an overview of different types of affective cues as means to elicit affective reactions and discuss the importance of their design for consumers' subsequent data disclosure decision evaluation (i.e., connecting phases 1 and 3 of the consumer privacy journey). Chapter 5 provides an overall discussion of the three essays and derives important implications for both research and practice. Finally, Chapter 6 comprises a brief conclusion. Figure 1.2 outlines the structure of my dissertation.

Figure 1.2. *Structure of The Dissertation.*

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2. Essay 1: New Technologies, New Tools, New Tensions: Deriving a Multistage Conceptualization of Consumers' Perceived Data Control in AI-Based Data Disclosure Settings

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New technologies create critical tensions, such as between providing consumers with greater control over their personal data and enhancing the technological sophistication of firms' offerings (e.g., through automation). Resolving such tensions requires specific, comprehensive conceptualizations and measures of consumers' perceived data control. Drawing from conceptual notions of control, as well as a behavioral control theoretical perspective, the authors develop a novel, multistage account of control across consumer–firm data exchanges (i.e., data flow and handling). Different control activities, pertaining to the collection, submission, access, and use of personal data, can be distinguished, defined, and operationalized to capture consumers' subjective control perceptions. Study 1, focused on quantitative measure validation, shows that consumers can distinguish the four data control activities; Study 2, a qualitative account using depth interviews, reveals that consumers identify the four control activities unprompted and across diverse contexts; Study 3, an experiment in the context of novel, automated data disclosure processes involving artificial intelligence (AI), reveals that consumers perceive a loss of control over personal data in the data flow and data handling stages, which decreases their willingness to enter the data disclosure process. Neither benefit perceptions nor reduced process effort offsets their reluctance to enter into AI (vs. non-AI) data disclosure processes. Collectively, these findings present both theoretical and practical implications.

2.1 Introduction

Recommendations about data privacy, from both academic research and business press, stress the imperative to provide control to customers. A recent global survey indicates that nearly 60% of consumers rank control as the most important determinant of their choice to disclose personal data to a firm, or rather, to enter a data disclosure process (EY, 2020). Consumers also appear more willing to comply with a data request when they perceive continuously high levels of control (Mothersbaugh et al., 2012; Phelps et al., 2000; Xu et al., 2012a). Following recommendations to provide customers with control over personal data interactions (e.g., Martin et al., 2017), many firms already design their data requests and processes explicitly to evoke high control perceptions (e.g., with privacy assurances; Gerlach et al., 2019; Xu et al., 2008). Despite this general consensus about the importance of control, the concept of control also has been subject to various definitions, applied to disparate firm tasks (e.g., usage), and used to characterize different data disclosure activities (e.g., collection, submission). That is, advocates recommend increasing consumer control to promote data privacy, but it is often unclear what control really means and how consumers perceive and interpret it in data-related interactions with a firm in various data disclosure settings.

Gaining a deeper understanding of consumer control perceptions is especially pressing in the face of evolving technological advancements. New technologies create novel, unstudied forms of data disclosure settings that may increase the tensions between the need to provide consumers with greater control during data disclosure processes and the goals of enhancing the technological sophistication of products and services and facilitating customer–firm interactions. Novel technologies, including those that rely on artificial intelligence (AI), allow for efficient processes and systems, sometimes by imposing limits on human input or

oversight—that is, by reducing consumer control (Quach et al., 2022). In this research, we focus on AI-based data disclosure processes, defined as services that collect and submit personal data for a specific purpose and benefit (e.g., customization) on behalf of customers, using sensors, videos, physical activity, and so forth. Retailers such as Amazon increasingly rely on such technologies (Amazon, 2022), which can facilitate customer interactions by reducing the process effort required of customers while also gathering personalized data (e.g., accurate measures of consumers' bodies for precise clothing fit). Consumers may appreciate the benefits of automated data technologies and processes, but they also may identify privacy control risks. In particular, decreased control perceptions represent a major risk, as seemingly “the most evident and best documented barrier to adopting autonomous technologies” (de Bellis & Johar, 2020, p. 77).

Even as it acknowledges that the loss of control leaves consumers reluctant to use AI-based technologies (Ameen et al., 2021; André et al., 2018; Leung et al., 2018; Puntoni et al., 2021; Schweitzer & van den Hende, 2016), AI literature fails to provide detailed empirical evidence about personal data control perceptions or how they relate to consumers' immediate and long-term perceptions of the benefits available in new AI-based disclosure settings. Instead, studies tend to focus on consumers' (decreased) control perceptions when they assess AI systems' output. This gap is surprising, in that AI-based technologies depend on (consumer) input data to operate and refine their intelligent products and services (Arnett, 2019; Morgan, 2019; Puntoni et al., 2021). Another concern arises from the tendency to treat perceived control over personal data as a one-dimensional construct (Malhotra et al., 2004; Xu et al., 2011), despite its appearance in various data exchange stages and activities. As privacy scholars recognize, consumers' control perceptions differ across stages of the customer–firm data exchange (Brandimarte et al., 2013; Martin

et al., 2017; Xu et al., 2012a; Zhao et al., 2012), yet we know of no conceptualization or differentiated operationalization of these perceptions. As a result, we lack a clear understanding of control perceptions in novel data disclosure settings, which means that firms lack insights into the best ways to implement new technologies while ensuring sufficient consumer control. To address these gaps, we pursue the following research goals:

- (1) Develop a novel, multistage perspective on consumers' perceived behavioral control over personal data, including precise definitions and operationalizations.
- (2) Examine consumers' specific control perceptions across various, novel data disclosure settings and processes, including those powered by AI.
- (3) Understand the contrast between consumers' perceived loss of control in new AI-based disclosure settings as it relates to perceived process effort and personalization benefits.

The initial idea for this study was inspired by discussions with a German online retailer that provides custom-fitted apparel and relies on advanced technologies. The firm recently integrated (optional) AI-based disclosure processes into its service, to personalize products and help users undertake self-measurement tasks with reduced process effort. Customer reluctance in response to this novel AI, despite its clear benefits and ease of use, sparked our research interest. Although the investigation subsequently grew beyond the parameters of the research partnership, we maintain a foundational focus on (1) consumer perceptions of control when confronted with AI-based (vs. non-AI) data disclosure requests, similar to those used by the focal retailer; (2) how control perceptions related to the data disclosure process affect long-term data handling control perceptions; and (3) how consumer

perceived benefits (immediate reduced process effort and long-term personalization benefits) relate to the loss of control over data activities across time.

We thus contribute to privacy literature (Adjerid et al., 2018; Bleier et al., 2020; Smith et al., 2011; Xu et al., 2012a) by defining, conceptualizing, and empirically validating a multistage model of control over personal data, which researchers can leverage to investigate control perceptions more precisely across data disclosure stages and settings. By examining prior conceptualizations, we clarify that control perceptions arise in relation to four activities linked to customer–firm data exchanges: personal data collection, submission, access, and use. We ground our work in a behavioral control theoretical perspective (Fishbein & Ajzen, 2009), to characterize the four control activities and distinguish control in active versus passive data disclosure settings. In addition, with a structured review of prior operationalizations of control, we measure the four identified control activities separately. The measurement model tested in Study 1 confirms that consumers can distinguish their own perceptions of control across these activities. Study 2 employs a qualitative, in-depth interview approach to gain deeper insights into consumers’ perceptions and knowledge of data control activities, as well as potential offsetting benefits; we thus can better distinguish active and passive data disclosure settings and establish new hybrid forms (e.g., involving AI-based processes). Study 2 also reveals consumers’ beliefs about their data control abilities in different disclosure situations and for different purposes (e.g., self-expression, customization, personalized ads).

Furthermore, we advance both privacy and AI literature by investigating control perceptions that pertain to AI-based services such as automated data disclosures. With Study 3, we consider consumers’ intentions to enter the data disclosure process in response to AI-based or non–AI-based data disclosure requests.

In both conditions, control over personal data appears to unfold through two time-bound activities: data flow, which consists of collection and submission control, and data handling, which resides with the firm and consists of access and use control. As we illustrate with Study 3, a loss of data flow control biases consumers' perceptions of data handling control and future personalization benefits, neither of which is affected by the AI, in an objective, behavioral control sense. Moreover, the negative effects cannot simply be counteracted by decreased process effort when consumers evaluate the situation in response to a data request. By moving beyond general privacy issues and concerns associated with AI-based systems (Ameen et al., 2021b; Davenport et al., 2020; Guha et al., 2021; Kopalle et al., 2022; Park et al., 2021; Tucker, 2019), we answer calls to address context-specific privacy questions, and in turn, we reveal how consumers respond to increasing privacy (control) losses due to the use of AI, as well as how they regard its benefits (de Bellis & Johar, 2020; Guha et al., 2021). By focusing on control over personal data, instead of a task or outcome, we provide a new account of the tensions between consumers and firms, as they relate to AI-based technologies (André et al., 2018; Puntoni et al., 2021; Schweitzer & van den Hende, 2016).

Practically, our research can increase firms' and regulators' understanding of and ability to strengthen consumers' control perceptions in AI-based data disclosure processes and contexts. It can also help them avoid implementing mechanisms that fail to address relevant control stages or do not convey meaningful consumer benefits. Our findings thus might help smooth tensions around consumer control and resistance, to make AI technology adoption and use more effective for firms, consumers, and policy makers.

2.2 Theoretical Background

With few exceptions, prior conceptualizations take a one-dimensional view of control over personal data. As a result of inconsistent definitions of control, its operationalizations also vary, involving disparate measures that capture control at different, unspecified stages. To date, we lack a comprehensive account of control in data privacy contexts—including definition, operationalization, measurement, and empirical analyses—that effectively acknowledge and consider individual, distinct stages and activities of control.

2.2.1 Multistage Conceptualization of Control

Control over personal data is one of the most extensively investigated, though still insufficiently defined, concepts in privacy research (Bleier et al., 2020).

Regardless of the perspective taken on control (e.g., privacy as analogous to control, control as a driver of privacy concerns, control as an independent construct), greater perceived control over personal data generally implies favorable customer outcomes, including enhanced disclosures (Mothersbaugh et al., 2012; Phelps et al., 2000; Xu et al., 2012a). Low levels of perceived control create negative customer reactions, such as unwillingness to disclose (Bleier et al., 2020; Smith et al., 2011).

Reflecting the lack of a universal definition of control over personal data, privacy literature offers a variety of conceptualizations (for reviews, see Xu et al., 2011; Xu et al., 2012a; see also Table 2.1). In general, previous studies acknowledge the existence of two sequential stages of consumer–firm data interactions, in which consumers might achieve control: over personal data flow and over personal data handling (Goodwin, 1991; Hoffman & Novak, 1999; Phelps et al., 2000; Xu et al., 2012a). Control over personal data flow involves the data disclosure process itself and whether, what, and how much data are disclosed if customers comply with a firm’s data request. In contrast, control over personal data handling pertains to what

happens to those personal data after they have been disclosed; it depends on who manages the disclosed data (e.g., recipient, third parties via data sharing or purchases) and how recipients employ them. The data disclosure process (usually) happens in the immediate future, right after consumers agree to enter the process, but data handling by the recipient occurs subsequent to (and depends on) the data flow stage, in the longer-term future.

However, early control research suggests that these two sequential stages also might be further divided into specific activities. Westin (1967, p. 7) cites consumers' ability "to control the terms under which personal information is acquired [collected] and used," consistent with the notion that control is a determinant of privacy concerns, such that "two expressions of control, awareness of information collection and usage beyond original transaction, are the predominant influences on the degree to which consumers experience privacy concern" (Sheehan & Hoy, 2000, p.63). Xu et al. (2008, p. 5) also define control as the "level of control over the disclosure [submission] and subsequent use of one's personal information."

In online social networks, another important aspect of control arises (Mosteller & Poddar, 2017; Tucker, 2014; Zhao et al., 2012), namely, being able to determine who has access to personal data after disclosure (i.e., who can see a post), which affects privacy-related decision-making. Brandimarte et al. (2013, p. 341) also argue that to understand consumers' perceptions of control over their personal data in a data exchange situation with a firm, "a distinction must be drawn between the release [submission] of personal information (the action of willingly sharing some private information with a set of recipients), access to it, and usage by others." These authors provide empirical evidence that a loss of control does not always have the same effect; decreased control over submitting data has a more negative effect on

consumers’ willingness to disclose personal data than does decreased control over data access and use by others.

Drawing from this review, we argue that an individual consumer can control four distinct activities in data interactions with a firm, beginning with the original data request by the firm and continuing to actions the firm takes with any disclosed consumer data. Conceptually then, control over personal data consists of control over data collection, submission, access, and use, as we define in Table 2.1.

Distinguishing these different control activities, related to the two stages of data flow (i.e., collection and submission) and handling (i.e., access and use), is critical for both measurement and interpretation efforts (Podsakoff et al., 2016).

Table 2.1. *Conceptualizing Control Across Consumer–Firm Data Interactions.*

Personal Data Control Activity	Definition	Examples from Prior Literature
Flow of personal data from consumer to recipient within the data disclosure process		
Collection	Consumers’ ability to influence the activity of gathering personal data (e.g., filling out a data form).	Caudill & Murphy, 2000; Günther & Spiekermann, 2005
Submission	Consumers’ ability to influence the activity of releasing personal data to distinct recipients (e.g., clicking “send” on a website to provide firms with collected data).	Brandimarte et al., 2013; James et al., 2015; Lwin & Williams, 2003
Handling of personal data by recipient after data disclosure		
Access	Consumers’ ability to influence the activity of determining who, other than the recipient, has access to their personal information after data disclosure (e.g., firms’ data-sharing activities with third parties in their business networks).	Mosteller & Poddar, 2017; Tucker, 2014; Zhao et al., 2012
Use	Consumers’ ability to influence the activity of determining how their personal information is used by the recipient after data disclosure (e.g., firms’ use of personal data for their own and explicit or implicit consumer benefits).	Mothersbaugh et al., 2012; Xu et al., 2008

Notes: Each of the cited studies refers to the relevant activity explicitly but not necessarily exclusively in its conceptualization of control over personal data.

2.2.2 Behavioral Control Theoretical Perspective

Search Exercising control in data disclosure settings is behavioral in nature, so to advance understanding of control as a multistage phenomenon comprised of

four constructs, we adopt a behavioral control perspective, as has been established in various research domains. According to relevant theory, behavioral control refers to people's understanding of "the degree to which they are capable of, or have control over, performing a given behavior" (Fishbein & Ajzen, 2009, p. 102). Consumers express high behavioral control if they can freely perform a behavior, by actively affecting or modifying an experience. With regard to control over personal data, we argue that consumers can only attain behavioral control of data collection and submission activities, and exercising control in these two stages requires distinct behaviors. Control over access and use resides with the firm, because consumers cannot perform these activities themselves. Despite not having actual behavioral control over data access and use, consumers might still perceive some control.¹ The possibility to exert control over data flow activities, from a control perspective, thus represents the main and essential difference between active and passive data disclosure settings. These settings have been distinguished by prior research into online data exchanges (Krafft et al., 2021), and with this novel perspective, we can also characterize new forms of data disclosure settings (e.g., hybrid forms; see Section 2.4.3 and 2.5).

In active data disclosure settings, such as firm-initiated data requests (e.g., signing up for a service) or consumer-initiated data disclosure settings (e.g., social media posts), consumers actively decide whether to enter into a data disclosure process and provide firms with specific information for distinct purposes (e.g., Bidler et al., 2020). In response to firm-initiated data requests, customers receive direct

¹ Due to legal requirements (e.g., General Data Protection Regulation [GDPR]), firms must inform customers about their data handling strategies (e.g., use of consumer data) and customer rights (e.g., right to be forgotten) before gathering data. Firms increasingly regulate themselves too, such as by adopting privacy seals (e.g., TRUSTe) to emphasize their data protection efforts. Such efforts influence consumers' control perceptions (e.g., Xu et al. 2008, 2011) but do not provide them with actual behavioral control over personal data.

benefits from data disclosure, such as personalized product offerings or monetary rewards. In consumer-initiated data disclosure settings, consumers often fulfill a personal need, such as self-presentation for social recognition, by disclosing their personal data. After deciding to enter a data disclosure process, they must carry out the task of gathering the personal data they will share with the recipient or platform, which implies high behavioral control over their personal data collection and submission. Thus, consumers can take responsibility for collecting the data (e.g., measuring physical body dimensions, selecting a picture, adding place information) and decide freely which data to submit (or not disclose).

In passive data disclosure settings, such as online tracking of consumer browsing behavior (e.g., click streams, cookie use, consumer searches or page views) or captures of mobile and geolocation data (e.g., Schumann et al., 2014), consumer data instead become a byproduct of the interaction. Often consumers are not even aware of passive data disclosures (Krafft et al., 2021). With passive data disclosure, consumers do not disclose personal data for a specific purpose; rather, the value that the firm provides in exchange for the disclosure tends to be indirect and not immediately perceptible by the consumer (e.g., improved customer experience in the online shop, personalized ads). Because data are automatically and often invisibly gathered throughout the interaction, consumers experience no behavioral control over personal data collection and submission, both of which are initiated by the firm and carried out automatically without active consumer involvement.

This behavioral perspective helps illustrate and isolate the specific ways consumers can exercise control in different stages and data disclosure settings, and also how consumers' perceptions of control may deviate from the control they actually have (i.e., behavioral control). In many cases, consumers perceive access and use control even when they cannot influence either dimension (Brandimarte et

al., 2013). Therefore, it is important to capture consumers' activity-related perceptions as potential drivers or inhibitors of data disclosure behavior, instead of just how they ought to perceive control, from a behavioral control theoretical perspective.

2.2.3 From Objective to Subjective and Behavioral to Perceived: Understanding Personal Data Control Operationalizations

Having reviewed prior definitions of control and identified four relevant control activities in consumer–firm data exchanges, we turn our attention to operationalizing and measuring control. To understand how prior research has operationalized control over personal data in different data disclosure settings, we conducted a structured review of marketing and information systems research. In line with prior literature (Choi & Land, 2016; Mothersbaugh et al., 2012; Xu et al., 2012a), we distinguish between dispositions of control over personal data (i.e., personal valuation of control) and contextual control perceptions (i.e., situation-specific evaluation of control). Our focus is on understanding consumers' control perceptions in distinct data disclosure situations, rather than general, personal dispositions with regard to control over personal data. As the summary of prior research in Table 2.2 illustrates, even when researchers acknowledge that control relates to different aspects of the data exchange (Brandimarte et al., 2013; Martin et al., 2017; Xu et al., 2012a; Zhao et al., 2012), they mostly measure it as a one-dimensional construct, defined in a variety of ways to reflect different forms of control (Li et al., 2017; Xu, 2007). Even more troubling, as Table 2.2 reveals, when control is defined as one-dimensional, it often is operationalized using measures that capture different activities of the data exchange. Empirical research also tends to prioritize the data handling stage (access and use; Krafft et al., 2017; Martin et al., 2017) but neglect the data flow stage (collection and submission).

The strong focus on access and use (i.e., data handling stage) is surprising, for two main reasons. First, consumers must enable data flow through collection and submission before the firm can exercise access and use. As Günther and Spiekermann (2005, p. 74) put it, “secondary use (and abuse) of information is not possible if access (data disclosure) is prohibited in the first place.” Second, when adopting a behavioral theoretical perspective on control, the actual behavior of providing third-party access to personal data and using the data after disclosure is limited to the data recipient (e.g., firm), beyond consumers’ behavioral control (even if they perceive control over it). Consumers can never actually execute behavioral control over personal data access and use, following an initial data disclosure. Their subsequent data control can only occur indirectly, because it must be granted by the firm (e.g., choice mechanisms to allow data sharing with third parties; information on firm-provided limits on data uses) or regulators (e.g., policy mandates enabling personal data modification requests, such as the right to be forgotten). Still, consumers might perceive erroneously that data handling is within their behavioral control. In particular, we anticipate that consumers perceive more control over access and use if they can execute behavioral control over the data flow stage. Furthermore, consumers might perceive control over data handling stages because firms and regulators actively offer “illusional” control, by providing choice options and more detailed information.

Table 2.2. Control Operationalizations: Key Insights from Prior Literature on Contextual Control Measures.

Personal Data Control Operationalization (Items per Stage)							
Citation	Context and Disclosure Form	Definition of (Perceived) Control	Collection	Submission	Access	Use	
Dinev et al., 2013**	Web 2.0; active	Consumers' beliefs in their ability to determine the extent to which information about themselves is released.	1	1	1	1	Other
Günther & Spiekermann, 2005	RFID technologies, passive	Consumers' awareness of being read and understanding when and why readouts are taking place (Spiekermann, 2007).	3				
James et al., 2015	Online social networks; active	Consumers' desire to control the disclosure of their information (information management) and interaction with others (interaction management).		5	3		
Krafft et al., 2017	Permission marketing; active	Extent to which consumers believe they can influence if and how personal data are used by a firm for marketing purposes (Mothersbaugh et al., 2012).				2	1

Key Takeaway
 Anonymity, secrecy, and confidentiality positively affect perceptions of control, increasing consumers' perceived privacy.
 RFID technologies decrease perceptions of control independently of privacy-enhancing tools, especially among highly educated consumers.
 Consumers can be clustered according to whether they have a higher need for information or interaction
 management control; the type and amount of data disclosed depends on personal preferences.
 Perceived control influences the probability of granting permission for interactive marketing activities, illustrating the importance for consumers to remain in charge of the provided information; no interaction between control and privacy concerns.

Krasnova et al., 2010	OSN; active	Consumers' ability to give permission for how their information can be used by the provider and other parties.	2	1	Perceived control affects consumers' trust in the OSN provider and other OSN members and adjusts risk perceptions.
Li et al., 2014	Healthcare technology (PHR); active	Perceived level of control over the disclosure and subsequent use of personal information (Xu et al., 2008).	2	1	Perceived control, representing a fairness lever, adjusts consumers' understanding of benefits and privacy risks of adopting standalone PHR.
Li et al., 2017**	Online website (vacation condo rental, consumer electronics); active	Perceived level of control over whether to interact with the firm's website and disclose personal information, what kind of personal information to disclose, and for what purpose by the firm.	1	1	Perceived control prompts liking emotions in consumers when interacting with an unfamiliar website; it moderates the relationship between privacy concerns and consumers' intentions to disclose data.
Liu et al., 2019	OSN; active	Perceived level of control over personal information manifested by voice (approval and modification) or exit (opt out) options (Caudill & Murphy, 2000).	1	2	Perceived control is negatively affected by role conflict of OSN users; habit and emotions moderate the relationship between role conflict and perceived control.
Lwin & Williams, 2003	Online data disclosure; active	Perceived behavioral control is a function of control beliefs and perceived facilitation, enabled by requisite resources and assessments of resource efficacy related to behavior (Ajzen & Madden, 1986).	3		Perceived behavioral control represents a significant driver of (false information) fabrication.

Martin et al., 2017	Online retailing (products and services); active	Consumers' perception of the extent to which they can manage a firm's use of their personal data (Tucker, 2014).	1	3	Perceived control and transparency suppress the negative effects of consumers' data vulnerabilities on cognitive and emotional trust.
Mosteller & Poddar, 2017	OSN; active	Perceived secondary control as the ability to determine how personal information is used and shared by firms, including with third parties.	2	1	Perceived secondary control fosters trust in OSN websites, which affects social media engagement.
Mothersbaugh et al., 2012	Online service; active	Extent to which consumers believe they can influence if and how personal data are used by a firm for marketing purposes.	3	3	Perceived control positively influences overall willingness to disclose, especially when perceived sensitivity of personal data is high versus low.
Ray et al., 2011	Online retailing; active	Perceived privacy control as a subdimension of security control, defined as consumers' belief that their disclosed sensitive information is not disclosed by the firm without permission.	3	1	Perceived security control, with privacy control as one subdimension, can be enhanced by firms' website investments, privacy policies and reputation; high control increases consumers' trust in online service providers.
Stone et al., 1983**, ***	Recipients of data (e.g., employer, insurance company); active	Consumers' ability to manage personal information in relation to other consumers, groups, or organizations.	1	1	Perceived control depends on the recipient of the data and affects consumers' willingness to disclose and to support legislation designed to regulate information handling by recipients.
Xu, 2007**	Location-based services; passive	Perceived control over disclosure and subsequent use of personal information; separate from privacy concerns.	1	2	Perceived control is a key influence on consumers' privacy concerns; can be addressed by privacy-enhancing technology and proxy control (industry self-regulation, government legislation).

<p>Xu et al., 2008**</p>	<p>E-commerce, OSN, financial and healthcare sites; active</p>	<p>Perceived control over disclosure and subsequent use of personal information; separate from privacy concerns.</p>		<p>1</p>	<p>2</p>	<p>1</p>	<p>Perceptions of control reduce consumers' perceptions of intrusion and subsequent privacy concerns; control can be addressed through privacy assurances and seals.</p>
<p>Xu et al., 2011**</p>	<p>E-commerce, OSN, financial and healthcare sites; active</p>	<p>Perceived control over disclosure and subsequent use of personal information; separate from privacy concerns.</p>		<p>1</p>	<p>1</p>	<p>2</p>	<p>Perceptions of privacy risk and privacy control, along with a personal disposition to value privacy, shape consumers' privacy concerns; control perceptions depend on contextual factors such as organizational privacy policies and participation in self-regulatory programs.</p>
<p>Xu et al., 2012a**</p>	<p>Location-based services; passive</p>	<p>Consumer's belief about the presence of factors that may increase or decrease the amount of control over the release and dissemination of personal information.</p>	<p>1</p>	<p>1</p>	<p>1</p>	<p>2</p>	<p>Perceived control over the collection and use of personal information affects context-specific privacy concerns of consumers; control perceptions can be addressed through consumer self-protection and government legislation, which differ in their effectiveness.</p>
<p>Zhao et al., 2012</p>	<p>Location-based social network services; active</p>	<p>Consumers' ability to control the social environment of disclosure and dissemination of personal data.</p>		<p>2</p>	<p>1</p>	<p>1</p>	<p>Feeling in control over personal data reduces consumers' privacy concerns better than being provided with privacy policies.</p>

Notes: We conducted a structured literature review using keywords such as “privacy” and “control OR autonom* OR *power* helpless* OR mastery OR supervis*”. Overall, we obtained 247 publications. After screening the publications and performing forward and backward searches, we included only those publications that measured perceived control over personal data in a contextual manner. In the table, the “Other” category refers to items that measure control in an overall manner or capture secondary control perceptions after data disclosure. OSN = online social network.

** Operationalizes control over personal data as a one-dimensional construct.

*** Stone et al. (1983) offer only examples of the 16 items they used to investigate consumers' control beliefs.

2.3 Study 1: Validating the Measurement of Control Perceptions

In Study 1, we test the base assumption that control can be conceptually divided into distinct stages during consumer–firm data exchanges, by determining if consumers perceive and can distinguish among the identified activities of collection, submission, access, and use control (i.e., perceive control over their personal data). We investigate control perceptions in four different, commonly experienced data disclosure settings that are actively initiated by the consumer and used for distinct purposes—which is why we expect respondents to have a good understanding of the specific settings. In turn, we increase the generalizability of the proposed conceptualization and operationalization of control over personal data.

2.3.1 Design, Participants, and Procedure

We recruited participants from a professional panel provider, Bilendi & respondi AG ($n = 266$; $M_{AGE} = 38.42$ years; $SD_{AGE} = 13.63$; 56% women) and presented them with four common and varied online data disclosure situations that reflect distinct data disclosure settings (i.e., firm-requested, consumer-initiated) and involve different automation levels. From the four scenarios, participants chose a situation that they had experienced themselves and could remember well (Appendix Table A2.2), namely: (1) using the online portal of an insurance company ($n = 67$), (2) using a smart voice assistant ($n = 58$), (3) creating a customer account with the help of an automatic field filling function ($n = 68$), and (4) posting on social media ($n = 73$). To ensure data quality and aid their recall, we asked participants to describe the disclosure process (see Appendix Table A2.2 for exemplary process descriptions); if they did not do so, they were excluded from the final sample.² Next, participants indicated their perceived control over the collection, submission, access,

² The initial sample featured 330 participants, but we excluded those that did not provide a process description (e.g., entered a random word in the description field to continue) or indicated that they did not remember the process.

and use of their personal data, which reflected items adapted from existing control operationalizations (see Table 2.2; Appendix Table A2.1). All constructs were measured on 7-point Likert-type scales (1 = “do not agree at all,” 7 = “completely agree”).

2.3.2 Results of Study 1

Model fit. Because the individual items for the four control stages reflect existing, adapted items from prior literature, we conducted an iterative confirmatory factor analysis (CFA) in AMOS 26, to clarify the different control items. The CFA encompasses all the data disclosure situations, based on our four-stage conceptualization of control over personal data activities. The final measurement model, with 12 items (3 items per stage; see Appendix Table A2.1), exhibits good model fit ($\chi^2/\text{d.f.} = 1.93$; confirmatory fit index = .985; goodness-of-fit index = .946; adjusted goodness-of-fit index = .912; Tucker-Lewis index = .979; root mean square error of approximation = .059; see Table 2.3). To test whether our full model, including four perceptions of control, fits significantly better than potentially competing reduced models, we conducted χ^2 difference tests (Gerbing & Anderson, 1988). We compared our full model against two reduced models, consisting of three dimensions in which we modeled collection and submission control as a single construct (Reduced Model 1) or collection and use control as single construct (Reduced Model 2). Then we compared it with a reduced model in which all control items loaded on a single factor (Reduced Model 3). The results reveal that the overall model fit for the full model is superior, and the χ^2 difference is significant for all combinations (see Table 2.3).

Table 2.3. *Model Fit for Full and Reduced Models, χ^2 Difference Test.*

	Full Model	Reduced Model 1	Reduced Model 2	Reduced Model 3
$\chi^2/d.f.$	1.93	4.32	12.26	25.18
CFI	.985	.944	.809	.566
GFI	.946	.869	.677	.437
AGFI	.912	.800	.507	.187
TLI	.979	.927	.753	.469
RMSEA	.059	.112	.206	.302
χ^2 difference Compared to full Model		$\Delta\chi^2 = 127.44,$ $\Delta df = 3,$ $p < .01$	$\Delta\chi^2 = 532.8,$ $\Delta df = 3,$ $p < .01$	$\Delta\chi^2 = 1256.5,$ $\Delta df = 6,$ $p < .01$

Notes: CFI = confirmatory fit index; GFI = goodness-of-fit index; AGFI = adjusted goodness-of-fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation. Reduced Model 1 = collection and submission control perceptions are modeled a single construct; Reduced Model 2 = collection and use control perceptions are modeled single construct; Reduced Model 3 = all items load on one construct.

Convergent and discriminant validity. Next, to evaluate the measurement model, we examine the convergent and discriminant validity of our reflective constructs (Table 2.4). Convergent validity indicates the degree to which different measures of the same construct correspond (Cook et al., 1979), so we use item reliability, construct composite reliability (CR), and average variance extracted (AVE) assessments. Item loadings exceed .82, indicating good item reliability (Appendix Table A2.1). The CR values exceed Nunnally’s (1978) .70 criterion, and the AVE values are all above .50, in support of the convergent validity of the measurement model. For discriminant validity, or the degree to which measures of different constructs are distinct (Campbell & Fiske, 1959), we tested whether the square root of the variance shared between a construct and its measures is greater than the correlations between the construct and any other construct in the model. All items achieve discriminant validity (see Table 2.4).

Then we evaluated the convergent and discriminant validity of each of the four scenarios. The results of a CFA that distinguishes the different scenarios indicate that three of the four scenarios performed similarly to the CFA for the whole

sample (Appendix Table A2.3); in the insurance setting though (Scenario 1), involving data disclosure by scanning or uploading documents about the participant’s health, we did not find discriminant validity for collection and submission control perceptions. From a consumer perspective in this scenario, the control perceptions pertaining to the data flow stage do not appear distinct but instead collapse, though participants’ process descriptions also illustrate that not all consumers experience this collapsing (see Appendix Table A2.2). Still, it is worth further investigation.

Table 2.4. *Measurement Scale Properties.*

Control over Personal Data	α	CR	AVE	Discriminant Validity			
				1	2	3	4
1. Collection	.89	.89	.74	.86			
2. Submission	.91	.91	.78	.82	.88		
3. Access	.94	.94	.82	.45	.51	.91	
4. Use	.95	.95	.86	.47	.50	.73	.93

Notes: α = Cronbach’s alpha; CR = composite reliability; AVE = average variance extracted.

2.3.3 Discussion of Study 1

Study 1 provides empirical support for our proposed conceptualization and operationalization of perceived control over personal data. Respondents can distinguish the four control perceptions that arise in consumer–firm data exchanges. These findings offer initial evidence showing, for the first time, that personal data control differs across distinct activities, as implied by prior conceptualizations. Consumers understand and appreciate their varying abilities to exercise control over data collection, submission, access, and use in different data disclosure situations. As we expected, and in line with behavioral control theory, the mean values for control perceptions in the data flow stage activities exceed those in the data handling stage for all four data disclosure settings (Appendix Table A2.1). Surprisingly, the means for access and use perceptions significantly differ from 1 (lowest scale point,

indicating perceptions of no control at all), which suggests that despite consumers' lack of behavioral control over access and use, some still perceive this ability.

Study 1 thus highlights the importance of studying data collection and submission control perceptions, which have been under-researched compared with data access and use control. This demand is especially critical when we consider that collection and submission control—though they differ conceptually, in an objective behavioral control perspective—might not seem distinct to consumers. Perhaps their simultaneous occurrence in automated data disclosure processes evoke this sense; when scanning a document within an app for example, data collection and submission happen at the same time. Thus, in such cases, we suggest an index of collection and submission control items for further investigations (i.e., data flow control index).

Notably, Scenarios 2 (voice assistants) and 3 (autofill function) also involve automation, yet in these cases, consumers perceive the two data flow control activities of collection and submission as distinct. Consumers arguably take a more active role when they have more options to control the automation (e.g., give commands, edit the filled-in information). We continue to examine all four control perceptions, but in line with our behavioral control theoretical perspective, we also emphasize control over data collection and submission as particularly relevant for additional investigation, in our effort to shed light on the conditions that explain when and why consumers perceive them as (not) distinct.

2.4 Study 2: Understanding Control Perceptions in Different Data Disclosure Settings

Study 1 supports our theorizing that consumers can distinguish the proposed conceptualization of perceived control over personal data. However, it remains unclear whether (1) different data activities related to data flow and handling across different data disclosure settings emerge from consumers unprompted, (2) consumers perceive the four activities as within their (behavioral) control, and (3) control perceptions differ depending on the data disclosure setting. Furthermore, even though our focus is on control activities in different disclosure settings, we also want to gain a better understanding of whether and how consumers evaluate the purpose of data disclosure (i.e., benefits of engaging in the process). This purpose not only represents a key distinction across data disclosure settings but also might help explain why consumers engage with automation. Study 2 aims to answer these questions.

2.4.1 Design, Participants, and Procedure

We conducted semi-structured depth interviews to gain meaningful insights into consumers' control perceptions in different situations. We stopped the data collection after no new insights emerged. Our final sample comprised 20 consumers of different ages, genders (11 women; $M_{AGE} = 36.35$ years), and educational and work backgrounds (see Table 2.5). The interviews were conducted via Zoom in November and December 2022. All participants gave their consent for the interviews to be audio recorded and were informed about how the interview data would be processed (e.g., recording deleted after 6 months in compliance with GDPR, confidential handling, no third-party access). After a brief introduction, we asked participants to describe their general thoughts and feelings about data disclosure, as well as various situations in which they encounter data disclosure. We began with

these broad questions to provoke general thinking about the topic. Next, participants had to select one of the data disclosure settings that they had mentioned and remembered well; we explicitly noted that they did not have to discuss any situation that made them feel uncomfortable. Participants detailed the data disclosure process, including their beliefs about what happens after data disclosure; they were invited to illustrate the sequence and process on a timeline, using the Zoom whiteboard. We asked participants to talk about their perceptions of control over personal data, based on this timeline, as well as why they entered the data disclosure process in the first place. Participants were not restricted to talking about one data disclosure situation; we encouraged them to talk freely and compare a specific situation with other situations if they wanted.

2.4.2 Results of Study 2

After transcribing the interviews, we coded them using the text analysis software MAXQDA. We applied a deductive approach (Hyde, 2000), drawing on data disclosure settings described in prior research (Krafft et al., 2021) and our predefined data activities (collection, submission, access, and use). The participants cited a variety of data disclosure situations, such as creating accounts on online shopping websites, posting pictures on social media, and being tracked on digital platforms (see Table 2.5), which reflect the general classification of active and passive data disclosure settings we described in Section 2.2.2. More participants chose to describe active data disclosure settings, which is not surprising, because they involve disclosure processes which tend to be more salient, whereas passive data disclosure processes are a byproduct of customer–firm interactions. This point is affirmed by our closer investigation of participants’ descriptions of the purpose of entering a data disclosure process, which we discuss after outlining findings related to consumers’ data flow and data handling control perceptions.

2.4.2.1 Data flow, active data disclosure processes

With regard to data flow activities, most participants mentioned control over both data collection and submission when they described active data disclosure situations. They also could name the type of personal data disclosed in any specific situation. Describing signing an online petition for charity, Participant 5 explained, “I simply filled out [the data form] indicating first name, last name, then address, phone number. But you weren’t forced to indicate them. And then, at the bottom, there was this checkbox you had to tick in order to agree to the privacy notices ... the stuff, which I just never actually read, and then I just clicked on ‘sign petition’.” Similarly, Participant 16 set up an online profile for one of her soccer players and noted, “I actually have high control over the personal data, from taking the picture to uploading it.” As expected, participants mostly perceived high control over the flow of their personal data (Table 2.5), unless those data were disclosed by someone else, as in the case of Participant 2 (Kamleitner & Mitchell, 2019). Interestingly, participants reporting on firm-initiated data disclosure processes expressed that, while they perceived high control over the activities of data collection and submission, control perceptions were reduced when the requested items were predetermined and without options.

2.4.2.2 Data flow, passive data disclosure processes

Participants who described passive data disclosure processes did not differentiate between collection and submission. Behavioral control theory differentiates them, but as we predicted in Study 1, consumers do not always perceive them as distinct. In addition, our participants reported limited perceived control over personal data flow; Participant 7’s perception was shared by many members of our sample: “This whole [data] tracking that runs in the background is just beyond my control.” Some participants, such as Participant 12, believed “The

moment I log on to the internet, I have no control over the data or over what the search engine or the platform I visit does with my data.... At best, I can hope that German or European platforms comply with the data protection law.” They sensed that control over personal data ends at the moment they enter the data disclosure process, whether they are using a service (e.g., smart voice assistant), searching on a website (e.g., keyword search on Amazon), or simply going online (e.g., opening an app or browser).

2.4.2.3 Data handling, active and passive data disclosure

All participants mentioned data handling activities when describing what happens after data disclosure. Regardless of the data disclosure setting (i.e., active or passive), consumers identify a lack of control over data access and data use activities, in line with our behavioral control theoretical conceptualization. Participant 11 illustrated this point with two metaphors: “it’s like a wall, so to speak, and [I] don’t know what’s actually happening with my data behind the wall,” and data handling is “a big cloud which is out of my visual range ... I have no control over it.”

2.4.2.4 Purpose of data disclosure

Participants’ initial purpose for disclosing personal data usually relates to the benefits they receive in exchange for and following their data disclosure (e.g., Bidler et al., 2020; Hui et al., 2007). In line with prior research, the benefits consumers receive can be direct or indirect, depending on the type of a data disclosure setting. In active settings, consumers disclose personal data for distinct purposes, such as to meet a specific intrinsic need or receive a direct benefit. Participant 1 posted on Instagram for “self-representation and to show off a nice picture”; Participant 17 used social media to present herself as a “hyper-esthetic” person and for socializing, especially during the COVID-19 pandemic. Other participants reported disclosing

data to create customer accounts and order products online, which provided the direct benefit of having products delivered to their homes.

In contrast, consumers did not report direct, specific benefits of passive data disclosure (e.g., consenting to being tracked online) but instead regarded it as an inevitable, automated process in online customer–firm interactions. For example, Participant 8, referring to searching for products on Amazon, acknowledged that “by searching for a keyword, my browser already disclose data, for instance, about the operating system of my computer.” In addition, some participants denied that data tracking offered any benefits, despite being able to use services or engage online. According to Participant 12, “I am aware that convenience [using the internet] always comes along with data being disclosed.” Others acknowledged benefitting indirectly from firms’ data tracking efforts, such as Participant 20’s recognition that he enjoys personalized ads and often buys products based on suggestions tailored to him.

2.4.2.5 New active, automated data disclosure

In some situations, consumers do not perceive control over data collection and submission, even if the settings appear active, in the sense that the processes are initiated by the consumer to fulfill a distinct purpose (Table 2.5), because the data disclosure processes also involve automation that assumes control over certain data activities. These novel data disclosure settings feature some characteristics of passive disclosure (i.e., automation) and largely result from firms’ efforts to employ technologies to design or complement traditional, active data disclosure processes. For example, Participant 6 reported high control over data collection in the process of completing a form to receive information about mortgages from a price comparison platform. During this data collection, she provided information about the house and “clicked ‘next’ and then I was asked for my name, address, availabilities

for scheduling a meeting and my e-mail address for sending an offer.... I didn't want to disclose that data and, thus, abandoned the process." As her data still were (automatically) submitted to the platform, which she learned when she was contacted by the platform, she perceived low control over data submission. In contrast, Participant 18 cited swiping his loyalty card at the checkout in a supermarket as control over personal data submission, though he did not perceive high control over data collection, because the cashier (not him) scanned the products he was buying.

With regard to Participant 19, who reported using a specific tax program to manage documents (i.e., scanning and uploading documents so the information can be automatically extracted), behavioral control theory would predict that, because the data submission takes place after data collection, it should result in high submission but low collection control perceptions. Instead, the participant perceived high control over both data flow activities. Taking the picture, in her opinion, was equivalent to collecting the data, and the automated extraction after submission appeared less salient to her. Similarly, Participant 10 reported that he had to scan his ID card to verify his identity to open a bank account but perceived high control over data flow activities, in that he transferred the automatically collected data himself by clicking a "submit" button. Finally, Participant 4 mentioned the control over data submission she attained by disabling the Bluetooth connection between her fitness tracker and smartphone: "oftentimes, I prefer to disconnect Bluetooth so that I have at least a little bit of control, because in so doing it just can't connect to the app." Yet she was aware that the sensors still collected her data (displayed on the tracker's screen) and accordingly reported low control over data collection. The purpose for entering a data disclosure process remains the same (e.g., checking fitness performance, managing tax documents), but automation can additionally allow for decreased

process effort, as Participant 14³ recognizes in relation to automated license plate recognition: “It’s very convenient. I drive to the car park, the gate opens. At the machine I have to enter my license plate number and pay.... Then, when I want to leave the car park, I don’t have to show some receipt as my license plate number is recognized automatically so the barrier opens automatically.”

2.4.3 Discussion of Study 2

Study 2 offers deeper insights into consumers’ perceptions and understanding of different data disclosure settings. Participants voluntarily mentioned varied specific data disclosure situations and could report, unprompted, the four conceptualized data activities (Table 2.5). Moreover, our results confirm that consumers perceive high control over data flows in active data disclosure processes but low control in passive data disclosure processes. They also could not distinguish data flow activities in passive data disclosure settings. Potential explanations include the simultaneous occurrence of the two activities, making their distinctiveness less salient, and that consumers are not (and have never been) actively involved in passive data disclosure processes, which may also apply to situations in which consumers anticipate control following a data request (e.g., Bleier et al., 2020; Günther & Spiekermann, 2005; Tucker, 2019). Thus, they would have little reason to reflect on these two activities. The absence of consumer involvement in data flow activities also is illustrated by our findings about the data disclosure purpose: Consumers in active settings enter a process to receive a specific benefit or satisfy a specific need; consumers in passive settings benefit only indirectly (e.g., personalized ads). With regard to data handling control, regardless of the data disclosure setting, consumers perceive low control over data handling activities, in

³ As mentioned previously, we encouraged participants to talk freely and did not restrict them from discussing different scenarios. This example is not the primary situation that Participant 14 described in the interview but an additional example he provided.

line with the Study 1 findings. They often confront information about both access and use (e.g., privacy notices), which may explain why those activities are salient, such that consumers can distinguish between the two activities, even though they are not actually involved in them (i.e., behavioral control resides with data recipient).

Finally, our findings reveal new forms of active data disclosure processes that assume (partial) control over personal data flow activities by integrating elements of passive data disclosure. In an attempt to facilitate data disclosure, firms increasingly rely on AI-enabled data disclosure processes that previously were performed by the consumer. This development decreases consumers' control over personal data collection and submission while simultaneously adding another benefit to data disclosure. The data disclosure purpose remains the same (e.g., receiving personalized feedback on fitness performance), but the process effort required to receive future benefits decreases. Thus, Study 2 affirms the external validity of our control conceptualization.

Table 2.5. Participant Characteristics, Data Disclosure Setting, Data Activities, and Control Perceptions.

ID	G	Age	Education	Employment	Data Disclosure Process	Specific Data Disclosure Situation*	Data Activity and Consumer Control Perception			
							COL	SUB	ACC	USE
01	F	22	A-Levels	Student	Active; non-automated	Social media posting by interviewee	✓, ↑	✓, ↑	✓, ↓	✓, ↓
02	F	20	A-Levels	Student	Active; non-automated	Social media posting by other person	✓, ↓	✓, ↓	✓, ↓	✓, ↓
03	F	21	A-Levels	Student	Active; non-automated	Registering on online pharmacy website to purchase products	✓, ↑	✓, ↑	✓, ↓	✓, ↓
04**	F	24	Bachelor Degree	Student	Active; non-automated	Registering on retailing website to purchase products	✓, ↑	✓, ↑	✓, ↓	✓, ↓
					Active; partially automated	Using a fitness tracker (bracelet)	✓, ↓	✓, ↑	✓, ↓	✓, ↓
05	F	28	State Examination (Pharmacy)	Employed (Medical Sector)	Active; non-automated	Signing a petition for charity	✓, ↑	✓, ↑	✓, ↓	✓, ↓
06	F	34	Advanced Technical College Certificate	Self-employed (Hospitality Industry)	Active; partially automated	Requesting information for mortgage financing	✓, ↑	✓, ↓	✓, ↓	✓, ↓
07	M	34	Technical School Degree	Employed (Construction Industry)	Active; non-automated	Purchasing products based on Google search results on a retailing platform	X; ↓		✓, ↓	✓, ↓
08	M	34	Master Degree	Unemployed	Passive; automated	Tracking behavior on a retailing platform based on initial keyword search	X; ↓		✓, ↓	✓, ↓
09	M	26	Master Degree	Employed (Public Service)	Active; non-automated	Registering on a retailing website to purchase products	✓, ↑	✓, ↑	✓, ↓	✓, ↓
10	M	47	PhD	Employed (Fashion Industry)	Active; partially automated	Verification of bank account and credit financing	✓, ↑	✓, ↑	✓, ↓	✓, ↓

11	M	28	Master Degree	Employed (Petrol Industry)	Active; non-automated	Purchasing products on platforms and websites	✓, ↑	✓, ↑	✓, ↓	✓, ↓
12	F	60	A-Levels	Employed (Metal Industry)	Passive; automated	Tracking search requests on Google	X; ↓	✓, ↓	✓, ↓	✓, ↓
13	F	43	University Diploma	Employed (Public Service)	Passive; automated	Tracking search requests and behavior on Google	X; ↓	✓, ↓	✓, ↓	✓, ↓
14.**	M	57	University Diploma	Self-employed (IT Consulting)	Active; non-automated	Setting up and curating a social media profile	✓, ↑	✓, ↑	✓, ↓	✓, ↓
15	M	50	State Examination (Teaching)	Employed (Public Service)	Passive; automated	Tracking technical and behavioral data on a social media platform	X; ↓	✓, ↓	✓, ↓	✓, ↓
16	F	31	State Examination (Teaching)	Employed (Public Service)	Active; non-automated	Tracking behavior and preferences on retailing platform	✓, ↑	✓, ↑	✓, ↓	✓, ↓
17	F	56	University Diploma	Self-Employed (Architecture Firm)	Active; non-automated	Creating a player's sports profile (other person; soccer) on a community page	✓, ↑	✓, ↑	✓, ↓	✓, ↓
18	M	28	State Examination (Law)	Employed (Law Firm)	Active; partially automated	Social media posting by interviewee of own content or reposting content from others	✓, ↑	✓, ↑	✓, ↓	✓, ↓
19	F	58	University Diploma	Consultant (Robotics Industry)	Active; partially automated	Using a customer loyalty card for a loyalty network (payback)	✓, ↓	✓, ↑	✓, ↓	✓, ↓
20	M	26	Bachelor Degree	Student	Passive; automated	Managing accounting documents in a tax program	✓, ↑	✓, ↑	✓, ↓	✓, ↓
						Tracking behavior and preferences on social media platforms	X; ↓	✓, ↓	✓, ↓	✓, ↓

Notes: G = gender; COL = collection; SUB = submission; ACC = access; USE = use; ✓ = activity mentioned; X = activity mentioned, no differentiation between COL and SUB; ↑ = high perceived control over activity; ↓ = low perceived control over activity.

**Data disclosure situation discussed in detail. **Participant discussed two data disclosure situations in detail.

2.5 Study 3: Perceived Control and Benefits in Active, AI-based Data Disclosure Processes

Prior research mainly investigates consumers' perceptions of control over personal data in well-established active or passive data disclosure settings (Krafft et al., 2021). Yet, as revealed in Study 2, hybrid forms of data disclosure, such as those involving active automated data disclosure processes, can assume partial data flow control. Thus, the automation of data flow activities, right after consumers actively enter the process, seems likely to exert long-term effects on control and benefit perceptions, as well as determine whether and how automation might provide benefits, related to diminished process effort, that counteract negative consumer perceptions. To investigate these questions, we use an example of a fashion retailing AI that automates data disclosure processes (i.e., collection and submission of personal data). In preliminary fieldwork conducted with the cooperation of a German online retailer, we sought to understand customer data disclosures across the AI and non-AI formats the company employs. After an initial data collection concerning consumers' decision to enter based on a data request (see Section 2.5.2), the retailer altered its technology offerings; we thus could not gather field data from the same customers. Instead, we used the retailer's real and pressing concerns about encouraging consumers to enter automated data disclosure processes to design Study 3 with strong external validity.

2.5.1 Hypotheses

The general goal of AI-based systems is to enable products and services to take over tasks, without intervention, that typically require human intelligence and decision-making (Agrawal et al., 2019; de Bellis & Johar, 2020; Puntoni et al., 2021). They can collect data through various sensors, videos, physical activities, and so forth; process them using statistical and computational methods; then provide

targeted outcomes (e.g., personalized recommendations). Therefore, we define AI-based data disclosure processes as services that perform personal data flow activities on behalf of consumers, using various tools, to leverage data flow for personalization and other purposes. These AI-based data disclosure processes can be characterized as active, because they pursue specific purposes and are actively initiated by the consumer. However, as demonstrated in Study 2, they differ from traditional, active forms of data disclosure and integrate some passive elements, because the AI-based service assumes behavioral control over the data collection (e.g., recording the customer's body to determine the fit of a shirt), then processes those data, such that it also assumes behavioral control over the data submission activity to provide targeted outcomes. We anticipate that consumers perceive this loss of behavioral control over data flow activities, which may decrease their intentions to enter the process, consistent with prior research on the negative behavioral effects of loss of control (Phelps et al., 2000; Song et al., 2016; Xu et al., 2012a). On the basis of our findings in Studies 1 and 2, showing that consumers collapse their collection and submission control perceptions, we further expect that they cannot distinguish the two activities and instead evaluate the data request at the moment they decide whether to enter a data disclosure process (i.e., no active involvement yet). Thus, we hypothesize:

H1: AI-based (vs. non-AI) data disclosure processes have a negative indirect effect on consumer intentions to enter the data disclosure process, through perceptions of diminished control over data flow activities.

From a behavioral control perspective, data access and use activities depend on the firm, regardless of the form of data disclosure setting (active or passive). However, Study 1 suggests that consumers perceive control over data handling to varying extents. As prior research shows, firms and regulators have implemented

mechanisms to create illusions of behavioral control (e.g., choice and information), which may increase data handling control perceptions (Martin et al., 2017; Xu et al., 2011). The control consumers perceive over the data flow stage also might bias their perceptions of the subsequent stage, such that even as consumers lose control over data collection and submission in AI-based data disclosure processes, they do not realize whether, what, and how much data actually are being disclosed. As Brandimarte et al. (2013) show, consumers who are not in control of data submission overestimate the risks of data handling activities (findings based on manipulating control rather than measuring control perceptions). Thus, offering a challenge to the behavioral control perspective, we hypothesize that a perceived loss of control over immediate data flow activities in the AI-based (vs. non-AI) data disclosure process decreases consumer perceptions of control over long-term, future data handling activities, leading to decreased intentions to enter the process.

H2: AI-based (vs. non-AI) active data disclosure processes have a negative indirect effect on consumers' control perceptions of a) access and b) use of personal data, through perceptions of diminished control over data flow activities.

A decrease in flow control perceptions in AI-based data disclosure processes also might affect personalization benefit perceptions, even though, from a behavioral perspective, the purpose of the data disclosure does not change. Privacy and personalization research (e.g., Awad & Krishnan, 2006; Chellappa & Sin, 2005; Cloarec et al., 2022) suggests that consumers' personalization benefit perceptions are constrained by privacy concerns or perceived privacy risks (personalization–privacy paradox). Based on this stream of research, we argue that a loss of immediate control over personal data flow activities in AI-based data disclosure processes might lessen consumers' perceptions of personalization benefits received in exchange for their

data disclosure, with a negative effect on intentions to enter the data disclosure process.

H3: AI-based (vs. non-AI) active data disclosure processes have a negative indirect effect on consumers' personalization benefit perceptions, through perceptions of diminished control over data flow activities.

A main reason to use AI-based systems is to reduce effort, in terms of time and work (Ameen et al., 2021a). In AI-based data disclosure processes, consumers thus might be inclined to use the service; measuring and collecting personal data to obtain personalization benefits can be effortful. Decreased effort drives AI adoption (de Bellis & Johar, 2020) and emerged as an automation-related process benefit in Study 2. Thus, we hypothesize that decreased process effort increases consumers' intention to enter the AI-based data disclosure process and functions as a conceptual and practical counterpart to perceived loss of control.

H4: AI-based (vs. non-AI) data disclosure processes have a positive indirect effect on consumer intentions to enter the data disclosure process, through perceptions of diminished process effort.

2.5.2 Design, Participants, and Procedure

As described, we obtained initial, basic, descriptive data from a retailer that suggested consumers are less prone to use AI-based data disclosure processes when they have a choice between automated or non-automated services. Of 10,071 online visitors who could use a service to determine their exact body dimensions and customize their clothing fit, 3,061 chose to allow the AI system to gather data, through video-based measures, whereas 7,010 preferred the non-AI option and took the measurements themselves. The Study 3 participants do not encounter any non-AI alternative, so their general likelihood to accept the AI format should be higher than

in the real-world choice design. Finding significant differences in perceptions of control between AI-based and non-AI conditions then would indicate an especially robust result.

To test the hypotheses, we employ a 2-condition (non-AI vs. AI-based data disclosure process) between-subjects design, to provide a conservative test of consumer reactions to different data disclosure processes. After excluding 20 participants who exhibited systematic response patterns (i.e., completed the study in less than 3 minutes, no variations in answers), we randomly assigned the final sample of 220 participants, recruited from Clickworker ($M_{AGE} = 42.09$ years; $SD_{AGE} = 11.60$; 47.3% women), to the treatments. In the online scenario, we manipulated data disclosure requests from a fictional online fashion retailer, “myshirt.” This setting is realistic; many fashion retailers employ non-automated, self-measuring services and have recently added AI-based data disclosure services to address industry challenges, such as high return rates (Amazon, 2022). In both conditions, the scenario indicated that myshirt was offering a new service that would allow customers to obtain an ideal fit for a shirt by providing eight body dimensions. To control for potential effects of time (Brough et al., 2022), participants could continue to answer the questions only after spending 20 seconds reading the data request.

Data requests for both conditions provided information about data flow and data handling to allow for informed decisions. We told participants in both conditions that eight body dimensions need to be taken to determine the ideal fit of their shirt or blouse. In the non-AI data disclosure condition, the data request explained to participants that the new service would provide step-by-step instructions on how to take the eight body dimension measurements themselves using a tape measure and submit them clicking “send data” (i.e., flow of personal data). In the AI-based condition, participants instead were told that the service offered by myshirt

would automatically determine the eight body dimensions based on a short video, then submit the data extracted from the video automatically on the customer's behalf. Information on access and use activities remained constant across conditions; the data request revealed that the measured body dimensions would only be used by myshirt for the purpose of providing personalized product recommendations and would not be shared with any third party (Appendix Table A2.4).

After the manipulation, we asked participants to indicate their intentions to enter the data disclosure process, using three items adopted from Malhotra et al. (2004), with 7-point semantic differential scales. Next, we asked for their control perceptions (see Study 1; all four constructs were queried to calculate an index for collection and submission), their personalization benefit perceptions using items adopted from Dinev et al. (2013), and their process effort perceptions using items from Franke and Schreier (2010). Finally, participants completed a manipulation check of their perceptions of the automation level on a 7-point semantic differential scale (1 = "not automated at all," 7 = "completely automated"). Appendix Table A2.6 lists all items.

2.5.3 Results of Study 3

Convergent and discriminant validity of control perceptions. We checked the convergent and discriminant validity of our reflective constructs based on a CFA using AMOS 26. Reflecting our predictions for H1 that consumers combine their collection and submission control perceptions when considering a data request, we calculated an index of the two stages of flow control. A CFA with flow, access, and use control perceptions indicates both convergent and discriminant validity for our measurement model (Table 2.6).⁴

⁴ To check if consumers perceive the two control activities as distinct, we also ran CFAs that model collection and submission control perceptions separately. The results show convergent

Table 2.6. *Measurement Scale Properties.*

Control over Personal Data	α	CR	AVE	Discriminant Validity		
				1	2	3
1. Flow	.94	.94	.72	.85		
2. Access	.94	.94	.85	.40	.92	
3. Use	.95	.95	.87	.48	.86	.93

Notes: α = Cronbach’s alpha; CR = composite reliability; AVE = average variance extracted.

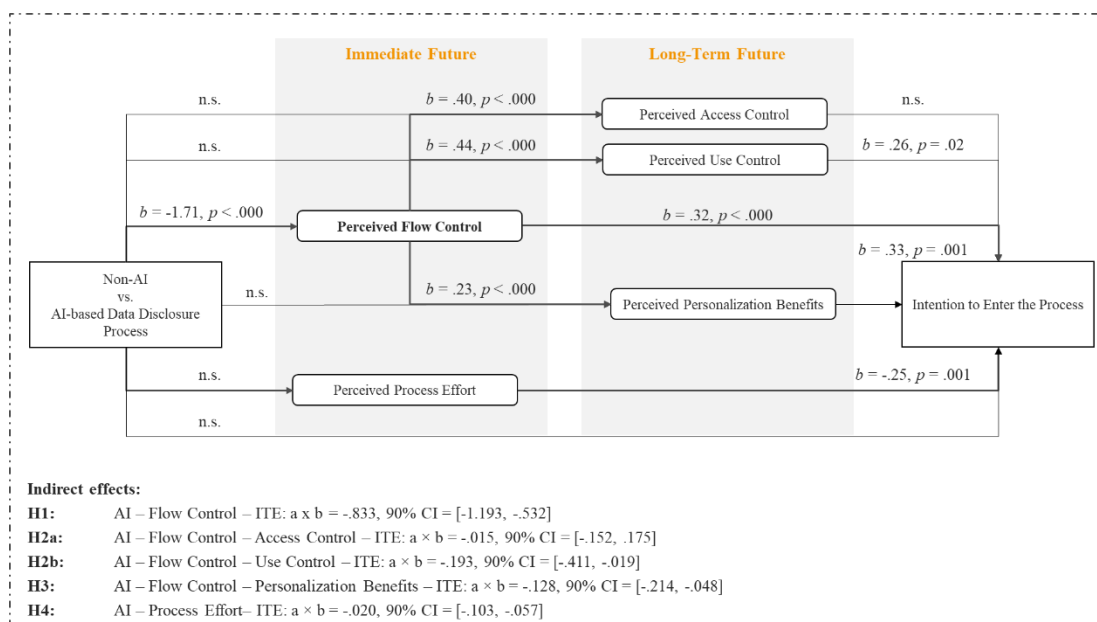
Manipulation check. An analysis of variance revealed that respondents perceived the AI-based data disclosure process as more automated than the non-AI data disclosure process ($F(1, 218) = 223.78, p < .001; M_{NoAI} = 2.49, M_{AI} = 5.46$).

Mediation analysis. Before investigating our hypotheses, we conducted analyses of variance and covariance on all variables in the model, controlling for age and gender (see Appendix Table A2.5). To test the hypothesized indirect effects, we used the PROCESS macro for SPSS (Hayes, 2018) and programmed a customized serial mediation model with 5,000 bootstrapping samples, creating a 90% bias-corrected confidence interval (CI). Age and gender were covariates. In support of H1, consumers’ intention to enter the process is mediated by perceived control over personal data flow ($a \times b = -.833, 90\% \text{ CI} = [-1.193, -.532]$). The results also reveal the predicted serial mediation path on intentions to enter through perceived flow and use control, in support of H2b (data disclosure process \rightarrow perceived data flow control \rightarrow perceived use control \rightarrow intention to enter the process; $a \times b = -.193, 90\% \text{ CI} = [-.411, -.019]$). However, the serial mediation path through perceived flow and access control is non-significant (data disclosure process \rightarrow perceived data flow control \rightarrow perceived access control \rightarrow intention to enter the process; $a \times b = -.015, 90\% \text{ CI} = [-.152, .175]$), so we cannot confirm H2a. For the serial mediation path through perceived flow control and personalization benefits, we find a significant

validity but not find discriminant validity, for this overall model or when investigating the scenarios separately.

effect, in support of H3 (data disclosure process → perceived data flow control → perceived personalization benefits → intention to enter the process; $a \times b = -.128$, 90% CI = [-.214, -.048]). With regard to perceived process effort as a potential counterpart to decreased control, we do not find a significant indirect effect though ($a \times b = -.020$, 90% CI = [-.103, -.057]), so we reject H4. All effects are summarized in our research model (Figure 2.1; see Appendix Table A2.7 for the values of the covariates).

Figure 2.1. Research Model, Results for Study 3.



2.5.4 Discussion of Study 3

In an online, scenario-based experiment, as expected, we find that participants do not differentiate between collection and submission control; they appear to evaluate control on the basis of information in the data request, when they are not (yet) actively involved in the process. At this point, participants did not know whether they would be obliged to detail all their body dimensions or what they were willing to share, whether they could abort the process, and so forth. The results from this study also support our first hypothesis: Presenting consumers with a request to disclose their data through an AI-based (vs. non-AI) data disclosure process for

personalization purposes decreases their control perceptions over the flow of personal data, driving the negative effect of AI-based data disclosure processes on intentions to enter the process (H1).

These decreased data flow control perceptions in turn bias consumers' long-term perceptions of access control and use control. Although we reject H2a, because no significant serial mediation occurs through flow and access control, in support of H2b, the decrease in perceived control over data use triggered by decreased flow control perceptions drives the negative effects on intentions to enter the process. This finding supports some prior evidence that data collection and use control strongly inform consumers' privacy-related decision-making (Malhotra et al., 2004; Sheehan & Hoy, 2000; Smith et al., 1996). They also affirm our claims about the importance of measuring different control perceptions. Ignoring consumers' anticipation of data handling control (access and use), with the assumption that it is not affected by specificities of the data disclosure process, as predicted by behavioral control theory, excludes relevant consumer perceptions and fails to account for their behavioral control preferences.

Turning to consumers' perceptions of immediate and long-term benefits when evaluating a data request, we find that decreased flow control perceptions also bias perceptions of personalization benefits gained from AI-based data disclosure processes (H3). This result reemphasizes the importance of measuring distinct control perceptions: The means for the AI-based results are higher than we might expect, but decreased flow control triggers insecurity about what data are shared and whether they ultimately provide the desired personalization benefits. Finally, we reject H4. Consumers do not perceive decreased process effort, representing an immediate benefit in AI-based processes. This finding might not generalize to all AI-based data disclosure settings (de Bellis & Johar, 2020; Puntoni et al., 2021), but in

our research context, decreased process effort does not make up for decreased control over personal data flow. These consumers do not perceive the process-related benefits of decreased effort when confronted with a data request.

2.6 Conclusion

Firms face a critical tension between balancing customers' multistage control needs and their own efforts to enhance the technological sophistication of their products and services. Marketing researchers, practitioners, and public policy makers need a comprehensive view of consumers' personal data control to understand their perceptions during consumer–firm data exchanges. Consumers' control perceptions map to four activities: data collection, submission, access, and use. They can distinguish among these different activities, over which they can exercise control (Studies 1, 2). We call on both research and practice to account for all four control activities; not every outcome predicted with an objective behavioral control theoretical perspective is perceived as such by the consumer. Collection and submission control perceptions combine when they appear effectively simultaneous, as well as when active consumer task involvement is not required, such as in automated data disclosure settings (e.g., passive and novel active AI-based processes) or when confronted with data requests (Studies 2, 3). As Study 3 illustrates, a loss of data flow control biases consumers' future perceptions of data handling control and benefits, neither of which differ due to the AI in an objective sense. Such negative effects cannot be counteracted by decreased process effort through automation based on consumers' understanding of a data request. A more precise understanding of control perceptions represents a necessary foundation for addressing consumers' need for control, especially in relation to novel technologies.

2.6.1 Theoretical Implications

This research offers three main theoretical contributions. First, we extend privacy research pertaining to control over personal data by introducing a multistage view of personal data control that maps onto the activities of the consumer–firm data exchange (i.e., collection, submission, access, and use control) from behavioral control theory (Fishbein & Ajzen, 2009). This critical advancement reflects the extent to which control is closely connected to overarching notions of privacy. Prior definitions tend to (implicitly) acknowledge the existence of four control activities but also confuse them, in both conceptualizations and operationalizations (Table 2.2). By clearly articulating the distinctiveness of collection, submission, access, and use control, through a behavioral control theory lens, we stress the importance of distinguishing control throughout consumer–firm data exchanges (i.e., data flow and data handling stages). Our structured review of control operationalizations also provides privacy research with robust, valid measures of the four control stages, and Study 1 empirically validates the proposed model. Consumers can distinguish control in each data activity, which is an important theoretical insight.

Moreover, we highlight the importance of relying on consumer perceptions (i.e., “subjective” lens) rather than just a behavioral control theory perspective (i.e., “objective” lens); they do not always align. Throughout our studies, in some circumstances (e.g., simultaneous activities, lack of active involvement), consumer perceptions of data flow activities collapse together. In Study 3, consumers perceive a loss of control over data activities (i.e., access and use control) that are not affected by the data disclosure process. Other consumers still perceive some non-zero level of control over data handling activities. Applying only an objective behavioral control lens to perceptions of control over personal data and limiting measures of control to a

single factor is likely to bias investigations of consumers' actual evaluations of different data disclosure settings.

Second, we contribute a deeper, more nuanced view of different forms of data disclosure settings and processes to privacy research (Bidler et al., 2020; Krafft et al., 2021). Adopting a behavioral control theoretical perspective helps us distinguish active versus passive data disclosure settings, based on consumers' ability to influence the data disclosure process. By integrating a benefits perspective (i.e., direct vs. indirect, depending on the data disclosure setting) into our theoretical framework, we also can clearly establish active versus passive forms, according to the data disclosure purpose. Comparing the loss of control, relative to the benefits accrued, enables us to identify novel forms of data disclosure, such as those described by participants in Study 2, that challenge research knowledge of consumers' privacy-related perceptions and behaviors. In Study 3, we provide first evidence that consumers' perceptions of personal data control activities in active data disclosure settings involving AI not only affect each other but also bias perceptions of the data disclosure purpose, namely, the benefits consumers receive in exchange for their data. Such effects cannot be counteracted by decreased process effort perceptions. These findings again stress the importance of a multistage control perspective on data disclosure settings.

Third, we contribute to AI literature. In automated data disclosure processes, the data themselves can be outcomes of an AI-based system and provide benefits based on their use (e.g., personalization). Most prior research treats data collection as a means to an end, not the core function of the AI-based system. By investigating consumers' data flow control perceptions, related to the immediate process, along with how these perceptions influence long-term expectations of data handling and future benefits, instead of focusing exclusively on future benefits or threats of AI-

based systems, we provide new insights into an important obstacle to AI-based product and service adoption (Ameen et al., 2021b; André et al., 2018; Schweitzer & van den Hende, 2016).

2.6.2 Practical Implications

Consumers' subjective perceptions often differ from the predictions of objective behavioral control theory (Fishbein & Ajzen, 2009), which requires firms and policy makers to carefully assess consumers' control perceptions and anticipate psychological outcomes, such as decreased benefit perceptions due to feelings of "being observed" (Puntoni et al., 2021), that also can lead to unfavorable behavioral outcomes. The distinct control perceptions of different activities along the customer–firm data exchange is especially important in data disclosure settings that involve new technologies that grant firms expanding options for collecting vast consumer data, then using those data in highly sophisticated manners (e.g., aggregation from different data sources; Quach et al., 2022). Such technologies (e.g., generative AI) are trending in the popular press, increasing the focus on and demands for data privacy (e.g., Forbes, 2023; Vice, 2022). Firms must be aware of and sensitive to control-related tensions that arise from the implementation of new technologies and design data requests and processes explicitly to strengthen customer control perceptions.

Policy makers also should work to smooth tensions for both consumers and firms. New privacy regulations to protect consumers could empower them with various control mechanisms, while also promoting healthy marketplaces. However, such policy levers and tools would be misguided without an adequate understanding of control. Even though many global privacy frameworks rely on control as a key consumer protective dimension (e.g., Steinhoff & Martin, 2022), our research reveals considerable nuance associated with providing consumers with meaningful forms of

control. Without understanding such nuance, regulators risk implementing ill-advised or ineffective protections related to control in consumer–firm data exchanges.

2.6.3 Limitations and Further Research

We investigate consumers' control perceptions following a data request, a setting that we chose explicitly because the decision to engage with the firm represents a crucial hurdle in data exchanges; once they have entered the disclosure process, consumers become more likely to disclose personal data (Bidler et al., 2020; Schumann et al., 2014). It also might be worthwhile to investigate other activities of control, beyond any specific consumer–firm exchange, such as secondary data use by third parties. Service providers collect data that vary in their sensitivity and at single versus multiple points in time, or even continuously (e.g., mood, emotion, fitness, conversation trackers; fitbit, 2022; Gizmodo, 2022; Moodfit, 2022). Furthermore, our Study 3 findings regarding consumers' perceptions of control could be extended to test the interdependence of the four control activities. As Günther and Spiekermann (2005) predict, access and use control perceptions might depend on the activities, pertaining to data flows. Another direction for research could include firm- and consumer-related variables that influence control perceptions, such as trust in the retailer, customers' technology readiness, or prior data breach experiences (Inman & Nikolova, 2017; Parasuraman & Colby, 2015).

With regard to finding additional mechanisms to counteract a specific loss of control over personal data collection, one interesting approach would be to investigate the influence of pre-installed privacy-enhancing technologies, such as those used widely to avoid digital advertising (Bleier et al., 2020). Such tools might increase consumers' sense of control (i.e., decreased feeling of being observed), because they limit overly intrusive data collection efforts by the firm, as a "powerful other" (Xu, et al., 2012b). But they also risk evoking a greater loss of perceived

collection control, because privacy protection gets allocated to yet another technology. Regardless of the specific direction, we hope research continues to study control as it manifests across all activities of consumer–firm data exchanges

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2.8 Appendices

Table A2.1. *Factor Loadings of Control Items and Means of Scenarios, Study 1.*

Dimension and Items	Factor Loading	Means (Scenario)
Control over personal data collection		
When using the <service or product>, I have control over...		
1. whether or not my personal data is collected. (Spiekermann, 2007)	.82	$M_{S1} = 4.40$
2. what personal data is collected. (Spiekermann, 2007)	.88	$M_{S2} = 3.66$
3. the amount of your personal data collected. (Xu, 2007)	.88	$M_{S3} = 5.11$ $M_{S4} = 3.89$
Control over personal data submission		
When using the <service or product>, I have control over...		
1. whether or not my personal data is submitted to the company. (Liu et al., 2019)	.82	$M_{S1} = 4.19$ $M_{S2} = 3.57$
2. what personal data is submitted to the company. (Xu et al., 2011)	.89	$M_{S3} = 4.76$
3. the amount of your personal data submitted to the company. (Xu, 2007).	.94	$M_{S4} = 3.64$
Control over personal data access		
When using the <service or product>, I have control over...		
1. whether or not my personal data is accessed by others after submission. (Martin et al., 2017)	.92	$M_{S1} = 2.68$ $M_{S2} = 2.90$
2. who can access my personal data after submission (Zhao et al., 2012)	.89	$M_{S3} = 2.62$ $M_{S4} = 3.22$
3. what personal data can be accessed by others after submission. (Zhao et al., 2012)	.92	
Control over personal data use		
When using the <service or product>, I have control over...		
1. what the company does with my personal data after submission. (Martin et al., 2017)	.95	$M_{S1} = 2.72$ $M_{S2} = 2.83$
2. how much the company uses my personal data after submission. (Martin et al., 2017)	.91	$M_{S3} = 2.66$ $M_{S4} = 2.60$
3. how my personal data is used by the company after submission. (Martin et al., 2017)	.93	

Notes: Five collection control items are adapted from Spiekermann (2007), who presents different collection control aspects in the context of RFID technologies. Reflecting our conceptualization of control over personal data flows in active data disclosure settings, we include items that refer to the data themselves (whether or not, which data are collected, and how much, adapted from Xu, 2007). The other items referring to “who” collects personal data and “how” personal data are collected achieve similar model fit and reliability values, but they do not reflect our focus on contextual (vs. dispositional) control or specific data disclosure settings in which the person who collects data and the way he or she does it is known.

Table A2.2. Scenarios and Exemplary Data Disclosure Process Descriptions, Study 1.

Data Disclosure Situation	Exemplary Process Description*
<p>Scenario 1: Using the online portal of an insurance company (app or browser version)**</p> <p>Please think about using your insurance company's online portal, where you can, for example, submit sick notes or participate in bonus programs. The following questions are about your perception of control regarding your personal data (e.g. sick notes, medical bills) in this situation.</p>	<ul style="list-style-type: none"> • "I had to scan the sick note with the app and then submit it." • "Very easy, scan document, upload, everything was protected through tan-login." • "I opened the app of my health insurance, logged into my account, and clicked on the button that led me to my targeted page; in this case, I wanted to upload my sick note and send it to my health insurance. I just had to photograph the sick note and confirm if I wanted to send it. Then I closed the app again, which was a very unbueraucratic process." • "I was informed in advance about the data protection regulations and agreed to them. Then I entered my data and sent it to the insurance company."
<p>Scenario 2: Using a smart voice assistant (e.g. Alexa, Siri)</p> <p>Please think about using a smart voice assistant (e.g. Alexa, Siri). The following questions are about your perception of control regarding your personal data (e.g. questions/ commands you ask/ give the assistant) in this situation.</p>	<ul style="list-style-type: none"> • "I asked a question and the Google Assistant answered me." • "I speak to the assistant and then my command is executed. In the process, the system identifies specific words that it has been trained on. If I use other commands, the system can't deal with them." • "Data collection is carried out through voice command...the data is submitted to the provider's servers by the device - the exact extent to which the data is processed is not apparent to the user." • "I give a voice command. The command is analyzed using reference databases and stored."
<p>Scenario 3: Creation of a customer account with the help of the automatic field filling function</p> <p>Please think of the creation of a customer account in an online store, in which their personal information was entered by means of the automatic filling function. The following questions are about your control perception regarding your personal data (e.g. name, address) in this situation.</p>	<ul style="list-style-type: none"> • "My name, as well as my address, was automatically filled in by the browser as soon as I entered the first letter of my first name. I entered the missing data manually." • "In the first field, you have to enter the first name. Once you have filled in the first letter of the first name, the rest will appear automatically. You just have to type in this field and the rest will fill in as well." • "I didn't feel very comfortable doing that. Although I know where the data comes from, I am always very shocked about how fast it is noticed that I want to enter my address data. I find it annoying because the data is sometimes entered in the wrong columns and I have to correct them later." • "I entered the first name entered and then clicked on the appearing information. Then my data was quickly entered, which I checked briefly. Now and then I have to enter my date of birth myself."

Scenario 4: Posting on social media

Please think about posting on social media. The following questions are about your perception of control regarding your personal data (e.g., the content of the post) in this situation.

- "I search for a picture in my [smartphone] gallery, then I'm asked if I want to allow it. After that, I edit the image and post it."
- "I upload a picture, add captions, make settings on who can see my picture, and submit it."
- "I opened the Instagram app on my phone. Then I clicked on the "create post" icon. After that, I had to select a picture from my gallery, which I did. Then I went one step further by clicking a button where filters can be selected for the picture. I kept the setting "no filter". After that, in the next step, I wrote a caption, linked people and indicated the location. Then I clicked on "post" and published the picture."
- "I wrote a post and then went to "my contacts" to indicate that only certain people can see it. Then I just posted it."

*Examples from participants' process descriptions, queried prior to questions about control perceptions.

** Examples in scenario 1 illustrate cases in which participants understood the distinction between collection and submission activities.

Table A2.3. *Measurement Scale Properties for Scenarios, Study 1.*

Control over Personal Data...	α	CR	AVE	Discriminant Validity			
				1	2	3	4
Scenario 1: Using the online portal of an insurance company							
$\chi^2/d.f.$ = 1.83; CFI = .948; GFI = .844; AGFI = .747; TLI = .928; RMSEA = .112							
1. Collection	.85	.85	.66	.81			
2. Submission	.91	.91	.78	.94	.88		
3. Access	.93	.94	.83	.52	.50	.91	
4. Use	.95	.95	.85	.52	.53	.71	.92
Scenario 2: Using a smart voice assistant							
$\chi^2/d.f.$ = 1.30; CFI = .984; GFI = .864; AGFI = .780; TLI = .978; RMSEA = .072							
1. Collection	.92	.92	.79	.89			
2. Submission	.94	.93	.83	.70	.91		
3. Access	.98	.98	.93	.48	.74	.96	
4. Use	.95	.95	.87	.57	.70	.93	.93
Scenario 3: Creation of a customer account with the help of the automatic filling function							
$\chi^2/d.f.$ = 1.18; CFI = .986; GFI = .884; AGFI = .812; TLI = .981; RMSEA = .052							
1. Collection	.85	.87	.69	.83			
2. Submission	.89	.89	.75	.80	.86		
3. Access	.90	.90	.76	.33	.30	.87	
4. Use	.95	.95	.87	.30	.31	.59	.93
Scenario 4: Posting on social media							
$\chi^2/d.f.$ = 1.51; CFI = .976; GFI = .869; AGFI = .787; TLI = .959; RMSEA = .084							
1. Collection	.91	.91	.77	.88			
2. Submission	.90	.90	.74	.82	.86		
3. Access	.93	.94	.83	.64	.62	.91	
4. Use	.95	.95	.85	.58	.53	.68	.92

Notes: α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; CFI = confirmatory fit index; GFI = goodness-of-fit index; AGFI = adjusted goodness-of-fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation

Table A2.4. Scenarios, Study 3.

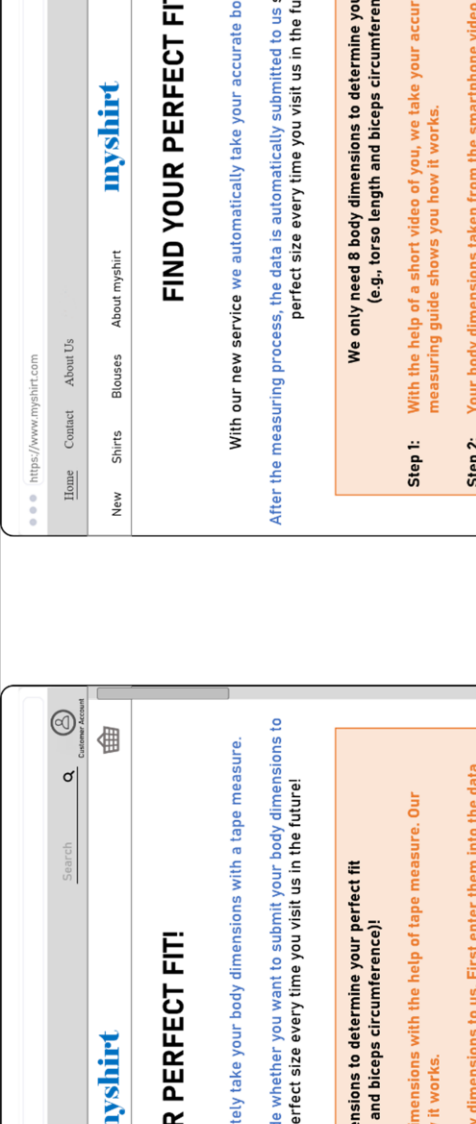
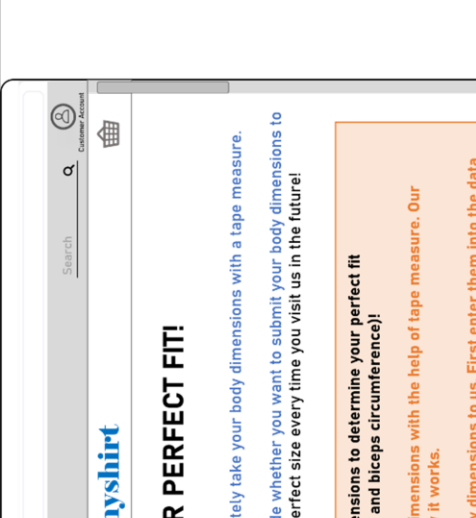
Non-AI Data Disclosure Process	AI-based Data Disclosure Process
 <p>FIND YOUR PERFECT FIT!</p> <p>With our new service we help you to accurately take your body dimensions with a tape measure.</p> <p>After the measurement process, you can decide whether you want to submit your body dimensions to us so that you can benefit from your perfect size every time you visit us in the future!</p> <p>We only need 8 body dimensions to determine your perfect fit (e.g., torso length and biceps circumference)!</p> <p>Step 1: Determine your accurate body dimensions with the help of tape measure. Our measuring guide shows you how it works.</p> <p>Step 2: Then submit your measured body dimensions to us. First enter them into the data form and then simply click on "Send data".</p> <p>Your exact body dimensions will be used to present you with the best fitting shirts and blouses.</p> <p>We will only use your data to provide you with the requested personalized content. We will not share your data with third parties.</p> <p>Scan the QR code to get the measuring guide to determine the 8 required body dimensions and submit them to us!</p>	 <p>FIND YOUR PERFECT FIT!</p> <p>With our new service we automatically take your accurate body dimensions for you.</p> <p>After the measuring process, the data is automatically submitted to us so that you can benefit from your perfect size every time you visit us in the future!</p> <p>We only need 8 body dimensions to determine your perfect fit (e.g., torso length and biceps circumference)!</p> <p>Step 1: With the help of a short video of you, we take your accurate body dimensions. Our measuring guide shows you how it works.</p> <p>Step 2: Your body dimensions taken from the smartphone video are submitted to us immediately. You do not have to do anything, because the submission of your data to us happens automatically.</p> <p>Your exact body dimensions will be used to present you with the best fitting shirts and blouses.</p> <p>We will only use your data to provide you with the requested personalized content. We will not share your data with third parties.</p> <p>Scan the QR code to have the 8 required body dimensions measured and submitted to us with the help of the video scan!</p>

Table A2.5. *Basic Effects With and Without Covariates, Study 3.*

DV	ANCOVA (Including Covariates)				ANOVA (Excluding Covariates)					
	Non-AI Process	AI-based Process	Main Effect	<i>F</i>	<i>p</i>	Non-AI Process	AI- based Process	Main Effect	<i>F</i> (1, 218)	<i>p</i>
Intention to enter	Adj. M(SE) 4.30 (.18)	Adj. M(SE) 3.22 (.18)	<i>F</i> 17.63	<i>p</i> < .001	<i>M</i> (SD) 4.32 (1.77)	<i>M</i> (SD) 3.18 (1.98)			19.94	< .001
Personalization benefits	5.37 (.11)	5.00 (.11)	5.50	= .02	5.39 (1.05)	4.98 (1.31)			6.54	= .01
Flow control	5.01 (.15)	3.30 (.14)	68.80	< .001	5.03 (1.44)	3.29 (1.59)			72.40	< .001
Access control	3.01 (.17)	2.68 (.16)	2.09	= .15	3.02 (1.76)	2.68 (1.68)			2.23	= .14
Use control	3.17 (.16)	2.60 (.16)	6.26	= .01	3.18 (1.75)	2.59 (1.59)			6.84	= .01
Process effort	3.70 (.14)	3.78 (.13)	.17	= .68	3.68 (1.43)	3.79 (1.41)			.33	= .57

Notes: ANCOVA = analysis of covariance ; ANOVA = analyses of variance.

Table A2.6. *Measurement Items and Reliability Assessment for Other Constructs, Study 3.*

Construct	Cronbach's Alpha	Measurement Items
Intention to Enter the Data Disclosure Process Adapted from Malhotra et al. (2004)	$\alpha_{Study3} = .98$	Please indicate whether you would comply with <i>myshirt's</i> invitation to enter the data disclosure process. 1. Unlikely/Likely 2. Impossible/Possible 3. Unwilling/Willing
Perceived Personalization Benefits Adapted from Dinev et al. (2013)	$\alpha_{Study3} = .85$	Using the service to determine my personal body dimensions... 1. could help me obtain more product suggestions and content I want in the future. 2. could help me get exactly the product suggestions and content I want. 3. could help me benefit from personalized product suggestions and content in the future.
Perceived Process Effort Adapted from Franke & Schreier (2010)	$\alpha_{Study3} = .92$	Determining my body dimensions would ... 1. be not complicated/ be complicated. 2. be easy to complete/ be difficult to complete. 3. require little effort / require a lot of effort. 4. take little time / take much time.

Notes: For all items, participants indicated their responses on seven-point Likert-type (1 = “strongly disagree,” 7 = “strongly agree”) or semantic differential scales.

Table A2.7. *Test Statistics for Covariates from ANCOVA and Mediation Analyses, Study 3.*

ANCOVA Study 3				
Dependent Variable	Age		Gender	
	<i>F</i> (1, 216)	<i>p</i>	<i>F</i> (1, 216)	<i>p</i>
Intention to enter	= .00	= .99	= 6.58	= .01
Personalization benefits	= .5.07	= .03	= 1.35	= .23
Flow control	= .001	= .97	= 1.97	= .16
Access control	= 1.80	= .18	= .74	= .39
Use control	= .11	= .74	= .89	= .35
Process effort	= 3.07	= .08	= .62	= .43
Mediation Model Study 3				
Dependent Variable	<i>b</i>	<i>p</i>	<i>b</i>	<i>p</i>
Intention to enter	= -.008	= .40	= .40	= .06
Personalization benefits	= .02	= .02	= .12	= .44
Flow control	= .0003	= .97	= .29	= .16
Access control	= -.01	= .15	= .09	= .70
Use control	= -.003	= .70	= .09	= .68
Process effort	= -.02	= .08	= -.15	= .43

3. Essay 2: Increasing Consumers' Willingness to Engage in Data Disclosure Processes through Relevance-illustrating Game Elements

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Encouraging consumers to enter a data disclosure process constitutes a crucial challenge for retailers. This paper suggests that retailers can leverage consumers' willingness to enter disclosure processes through the design of their data requests. Four experimental studies confirm that consumers are more likely to comply with a data request if retailers do not only use textual relevance arguments but also augment them with relevance-illustrating game elements to further underpin the purpose of data disclosure. This favorable effect can be delineated according to dual-processing models of decision-making: Relevance-illustrating game elements amplify the positive effect of textual relevance arguments by helping consumers to a) cognitively appreciate the objective benefits of data disclosure (i.e., meaningful engagement) and b) increase hedonic engagement on the affective processing route. However, arbitrarily chosen game elements which solely aim at entertaining without conveying the purpose of data disclosure, do not yield these positive effects. Finally, the authors show that the proposed approach is especially worthwhile for retailers facing customers with low trust levels, whereas customers with high trust levels are likely to comply with the data request regardless.

3.1 Introduction

With detailed consumer profiles, retailers can match their products to consumers' sociodemographic traits and personal interests, such that their offers are more relevant to consumers and hence more profitable for the firm (Schumann et al., 2014). Thus, gathering and exploiting consumer data for personalization purposes constitutes a crucial competitive advantage for retailers in the modern, digital landscape (Bradlow et al., 2017; Martin et al., 2020). However, due to the widespread proliferation of data collection efforts and undermined confidence in retailers concerning those efforts, consumers increasingly express negative attitudes towards data disclosure (Culnan & Armstrong, 1999). This negative attitude constitutes a challenge for retailers who try to convince consumers to enter their data disclosure processes. Empirical evidence showed that entering the data disclosure process is the crucial bottleneck and that increasing the number of consumers who start a data disclosure process is the most significant lever (Joinson et al., 2007; Schumann et al., 2014). For example, Schumann et al. (2014) found that less than 1% of users clicked on online service providers' survey invitations; whereas, once a survey was started, 23.7% of users finished it. Similarly, Joinson et al. (2007) report that only 6,9% of participants who began an online questionnaire did not finish it. Thus, retailers confront the challenge to design requests that encourage consumers to enter the data disclosure process in the first place.

In order to increase consumers' willingness to engage in data disclosure, practitioner-oriented studies highlight the importance of communicating the direct benefits of data disclosure to consumers: 83% of adult consumers would be willing to disclose their data for personalization purposes if retailers clearly stated how those data would be used and communicated a direct linkage between the disclosed data and resulting benefits (Accenture Interactive, 2018; Data & Marketing Association,

2018). Based on these insights, many retailers such as Nike, Urban Outfitters, Guess, and Converse employ textual relevance arguments in their data requests such as “We use these details to [...] personalize your Urban Outfitters experience so you can easily find what you are most interested” (Urban Outfitters, 2020) or “We [...] use this information to send you personalized marketing communications” (Guess, 2020). Such textual relevance arguments convey the purpose of data disclosure (e.g., data disclosure for personalization purposes). However, prior studies also show that including textual relevance arguments as statements in a data request does not guarantee data disclosure: Consumers often distrust retailers and doubt that they would actually benefit from the disclosure as the retailer declares (Data & Marketing Association, 2018). Reasons for low levels of trust are manifold and cannot always be controlled by retailers (Beldad et al., 2010; Selnes, 1998; Yoon, 2002): (New) consumers might not have established a trustworthy relationship with the retailer (yet), there might have been negative word of mouth (WOM), or consumers might simply be very cautious. Due to such factors it is hard for most retailers to convince consumers to believe statements in data requests pertaining to future personalization benefits.

To overcome this hurdle and support consumers’ appreciation of the future benefits of disclosure (i.e., to make consumers believe the textual relevance argument), we propose to facilitate textual relevance arguments with easily processable and illustrative cues. Gamification literature offers a promising approach to accomplish this goal. In general, gamification refers to a process of enhancing a service with motivational affordances (i.e., game elements such as avatars, icons, and points) for experiences similar to those created by games (Huotari & Hamari, 2017; Koivisto & Hamari, 2019) in order to affect consumers’ psychological states (Hamari, 2013; Huotari & Hamari, 2012; Jung et al., 2010; Zhang, 2008). As such,

retailers increasingly recognize the effectiveness of gamification as a lever to facilitate favorable consumer behavior (e.g., Berger et al., 2018; Liu et al., 2017; Müller-Stewens et al., 2017; Richter et al., 2015; Thorpe & Roper, 2019). However, gamification approaches based on the mere addition of game elements to elicit immediate enjoyment might result in negative consumer perceptions, as in the example of Zappos: The online retailer was criticized for implementing game elements that had no purpose for their customers which led to a quick end to the program (eLearning Industry, 2017). To attain favorable consumer behavior, retailers should avoid game elements that are unrelated to a specific situation and only strive to be entertaining (i.e., purely hedonic game elements). Instead, retailers should employ relevance-illustrating game elements that are tailored to the specific data disclosure situation (Eisingerich et al., 2019) to convey the purpose of data disclosure (i.e., data in exchange for personalization benefits). This can be achieved by choosing game elements that summarize the requested data in an affective and easily processable manner to allow consumers to envision how their data is used. A retailer requesting data for personalization purposes in the fashion context, for example, could employ avatars which summarize the disclosed data by reflecting the physical appearance of the consumer. This in turn helps consumers to better understand how the disclosed data might lead to personalization benefits in the future—that is, the avatar illustrates the relevance of data disclosure.

This approach of combining textual relevance arguments with relevance-illustrating game elements can be delineated according to dual processing models of decision-making (Epstein, 1994; Evans & Stanovich, 2013; Shiv & Fedorikhin, 1999). Dual-processing models propose that consumers base their decisions on two parallel routes: a cognitive and an affective processing route. These two routes correspond well to our proposed approach. By augmenting textual relevance

arguments with relevance-illustrating game elements, retailers help consumers to more easily appreciate objective disclosure benefits (i.e., cognitive processing route) while at the same time, providing entertaining experiences (i.e., affective processing route).

Literature on data disclosure (for a literature review see Smith et al., 2011) as well as on gamification (for a literature review see Koivisto & Hamari, 2019) offers extensive insights. We propose that by integrating these research streams, we contribute to both streams as well as address practical issues pertaining to consumers' reluctance to enter disclosure processes. We pursue three main research goals:

- (1) Investigate the effectiveness of relevance-illustrating game elements to facilitate textual relevance arguments in order to increase consumers' data disclosure intentions.
- (2) Delineate the underlying psychological mechanism according to a dual-processing model.
- (3) Investigate trust as a contingency factor for the effectiveness of relevance-illustrating game elements for retailers facing low vs. high trust customers.

To pursue our research objectives, we focused on the fashion-retail context as it highly relies on consumer data to personalize offers in order to address current challenges in the industry, (e.g., growing consumerism and a highly competitive landscape) (Infinity Research, 2019; Women's Wear Daily, 2019). Results from four experiments contribute to the literature in several ways: First, we contribute to retailing literature regarding consumers' acceptance of direct marketing approaches, such as personalization and online targeting (Goldfarb & Tucker, 2011; Milne & Gordon, 1993; Schumann et al., 2014). By integrating approaches from privacy-related decision-making literature and gamification literature, we show the

effectiveness of facilitating textual relevance arguments with relevance-illustrating game elements to foster consumers' willingness to enter a disclosure process.

Further, our results advance the emerging research stream that advocates for the importance of affective processing in privacy-related decision-making (Alashoor et al., 2018; Dinev et al., 2015; Gerlach et al., 2019; Kehr et al., 2015; Li et al., 2011; Wakefield, 2013) by delineating consumers' decision-making according to a dual-processing model (Epstein, 1994; Evans & Stanovich, 2013; Shiv & Fedorikhin, 1999). Specifically, we argue that consumers' evaluations of cognitive arguments (i.e., textual relevance arguments) need to be facilitated through the use of affective, easily processable hedonic cues (i.e., relevance-illustrating game elements). Finally, by uncovering consumers' anticipation of meaningful and hedonic engagement as two strong drivers of consumers' decision-making, we advance gamification literature, which has so far mainly focused on the hedonic aspects of gamification (Csikszentmihalyi, 1990; Hamari et al., 2016; Liu et al., 2017; Müller-Stewens et al., 2017; Rettie, 2001). Beyond the expansion of retailing, data disclosure, and gamification literature, this study also highlights implications for practice: We introduce a data collection approach that is superior to common ways of data collection for both consumers and retailers alike as it fosters consumers' perception of future personalization benefits and ultimately leads to higher disclosure intentions among those consumers. Subsequent sections comprise our theoretical background, hypotheses development, data collection procedures, moderated mediation analyses, and discussions of each of the experimental studies. We conclude with a general discussion of the findings, limitations, and avenues for further research.

3.2 Theoretical Background and Hypotheses Development

3.2.1 Data Disclosure: The Privacy Calculus

Based on the perception of privacy as a tradable commodity (Smith et al., 2011), consumers conduct a risk–benefit analysis when confronted with the decision to disclose data in exchange for economic or social benefits (Culnan & Armstrong, 1999; Dinev & Hart, 2006). This approach to explain individuals' data disclosure is called the privacy calculus framework (Smith et al., 2011). It assumes that consumers consider the consequences, such as perceived risks or benefits of data disclosure, before they make a situation-specific decision (Laufer & Wolfe, 1977). In general, privacy calculus literature focuses on consumers' willingness to disclose data (Smith et al., 2011); it does not explicitly investigate consumers' decision-making underlying their willingness to enter a data disclosure process.

Nevertheless, current industry practice uses some general principles from literature on disclosure intentions to encourage consumers to enter the disclosure process. Following the logic of the privacy calculus, retailers can employ two approaches to foster data disclosure intentions (Hui et al., 2007). First, retailers can address consumers' risk perceptions and minimize factors that deter consumers from disclosing their personal data, such as highlighting their efforts to protect consumers' privacy. Second, retailers can provide and highlight benefits that motivate consumers to enter data disclosure processes. The effectiveness of using situational factors to increase disclosure intentions by adjusting risk perceptions has been demonstrated in studies that consider data sensitivity (Lwin et al., 2007; Phelps et al., 2000), control over data (Culnan, 1993; Smith et al., 1996), and privacy assurances (Hui et al., 2007). However, recent research on the effectiveness of situational cues such as privacy assurances suggests that the implications for data disclosure are limited, with positive effects disappearing after only a few seconds (Acquisti et al., 2013).

Regarding the leverage of disclosure intentions through consumers' perception of benefits, both theory and practice suggest using monetary or time-saving incentives in exchange for participation in data disclosure tasks (Hui et al., 2007; Xu et al., 2009). The downside is that consumers might believe they were tricked into the disclosure (Dinev et al., 2015). Specifically, consumers might regret participating in the data disclosure in exchange for a coupon, after having reflected on the decision and its long-term impact compared to the short-term benefit of the coupon (Dinev et al., 2015). Thus, such approaches fail to address consumers' need for a direct link between the disclosed data and the resulting benefits (Accenture Interactive, 2018; Data & Marketing Association, 2018). But even if retailers communicate this direct linkage—i.e., convey the relevance of data disclosure—such relevance arguments cannot guarantee data disclosure because consumers often doubt retailers' promises pertaining to future benefits (Data & Marketing Association, 2018). To address the challenge of facilitating consumers' appreciation for future benefits, retailers should help consumers to reflect on the relevance of data disclosure. To achieve this goal, retailers might use easily processable, affective cues to facilitate relevance arguments—as proposed by gamification literature, which has been shown to elicit favorable consumer behavior in various contexts (e.g., Berger et al., 2018; Müller-Stewens et al., 2017).

3.2.2 Gamification

Today, more and more firms try to encourage positive outcomes, such as accelerated repurchases, engagement, and retention, by integrating game elements into their customer interactions (Hofacker et al., 2016). This process of enhancing a service with motivational affordances for experiences similar to those created by games is denoted as gamification (Huotari & Hamari, 2017; Koivisto & Hamari, 2019). Game elements can take many forms and shapes: They range from points,

badges, and leaderboards to feedback and status, narratives, challenges, competitions, rewards, and avatars (e.g., Blohm & Leimeister, 2013; Hamari et al., 2014; Werbach & Hunter, 2015). A sophisticated use of game elements might help firms induce positive psychological and behavioral outcomes (Berger et al., 2018; Müller-Stewens et al., 2017). Prior studies showed, for example, that gamification positively influences consumers' inclination to consider adopting innovations (Müller-Stewens et al., 2017), enhances the likelihood of loyalty program use (Kim & Ahn, 2017), or facilitates data disclosure in the case of location-based photo sharing (Montola et al., 2009).

Based on findings from various domains, the use of gamification seems to be a reasonable approach to foster consumers' privacy-related decisions. However, employing game elements with the primary goal to entertain consumers, while actually focusing on firm-related outcomes, might lead to negative consumer perceptions: Retailers who fail to tailor game elements to the specific disclosure situation, risk consumer perceptions of betrayal because consumers believe they were tricked into data disclosure (Deterding, 2012).

3.2.3 Using Relevance-illustrating Game Elements to Facilitate Textual Relevance Arguments

To overcome the boundaries of the effectiveness of privacy approaches and gamification approaches respectively, we propose to combine them. Specifically, we argue that retailers should design data requests to not only communicate the direct linkage between the disclosed data and resulting benefits (i.e., textual relevance argument) as is common industry practice. Rather, retailers should augment these textual relevance arguments with game elements (Agarwal & Karahanna, 2000; Eisingerich et al., 2019). In order to be effective, these game elements need to be tailored to the textual relevance arguments such that they illustrate the direct benefits

in an easily processable manner (Eisingerich et al., 2019). Typical game elements tailored to the relevance argument of personalization could be personal avatars, icons, and badges, which summarize the requested data on consumers' physical appearance, interests, and financial aspects (Reeves & Read, 2009). We refer to such tailored game elements as relevance-illustrating game elements, because they are not only entertaining—as suggested by gamification literature—but also help consumers to understand the purpose (i.e., the relevance) of data disclosure. Following this line of reasoning, we contend that data disclosure requests conveying the purpose of disclosure through both a textual relevance argument and through relevance-illustrating game elements, amplify positive effects found in the privacy (e.g., Culnan & Armstrong, 1999; Dinev & Hart, 2006) and gamification domains respectively (e.g., Berger et al., 2018; Müller-Stewens et al., 2017).

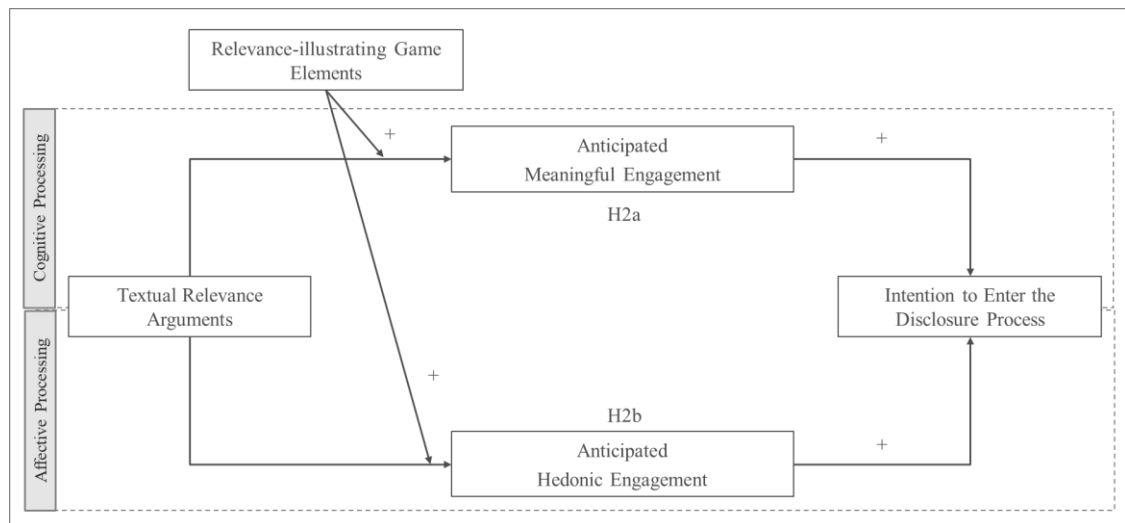
H1: Presenting consumers with a data disclosure request that facilitates textual relevance arguments with relevance-illustrating game elements, increases consumers' likelihood to enter the data disclosure process in contrast to common industry practice of only using relevance arguments.

3.2.4 Dual Processing: The Mechanism Underlying the Effectiveness of Facilitating Textual Relevance Arguments with Relevance-illustrating Game Elements on Disclosure Intentions

We argue that augmenting textual relevance arguments with relevance-illustrating game elements amplifies positive effects on consumers' willingness to comply with data disclosure requests. These two components—textual relevance arguments and relevance-illustrating game elements—correspond well to established theory on decision-making through dual-processing (Epstein, 1994; Evans & Stanovich, 2013). Dual-processing literature proposes that consumers process

decision-making tasks through two parallel systems: The first system is a fast, automatic process accounting for affective reactions (i.e., affective processing), whereas the second system processes objective aspects in a deliberate, cognitive manner (i.e., cognitive processing). In accordance with this perspective on consumers’ decision-making through two systems, we propose that data disclosure requests where textual relevance arguments are facilitated through relevance-illustrating game elements might trigger both affective and cognitive processing. Figure 3.1 illustrates our proposed dual-processing model as well as the forthcoming hypotheses.

Figure 3.1. *Dual-processing Model.*



Cognitive processing. As the examples in the introduction illustrate, retailers often seek to convey the purpose of data disclosure by using textual relevance arguments. Such textual relevance arguments aim at increasing consumers’ understanding of the current disclosure situation and corresponding benefits (i.e., future personalization benefits in exchange for data). Such a state of mind, in which consumers experience a sense of meaning and more deeply understand the relevance of an event or behavior, is denoted as meaningful engagement (Dewey, 1934; Liu et al., 2017; Nicholson, 2013). As per this definition, meaningful engagement reflects consumers’ cognitive processing of the objective aspects related to the data

disclosure request (Eisingerich et al., 2019; Liu et al., 2017; Suh et al., 2017). These cognitive evaluations can be enhanced by providing consumers with easily processable cues that facilitate textual relevance arguments (Culnan & Armstrong, 1999). Relevance-illustrating game elements can be considered as such easily processable cues (e.g., Berger et al., 2018; Eisingerich et al., 2019; Müller-Stewens et al., 2017). Hence, by augmenting textual relevance arguments with relevance-illustrating game elements, retailers help consumers to appreciate objective disclosure benefits—that is, consumers might more easily anticipate meaningful engagement. Greater meaningful engagement in turn should motivate consumer behavior (Suh et al., 2017) such that anticipation of meaningful engagement should increase consumers' intentions to enter the data disclosure process.

Affective processing. Augmenting textual relevance arguments with relevance-illustrating game elements will not only increase consumers' anticipation of meaningful engagement, but will also trigger an affective reaction. According to dual-processing literature (Epstein, 1994; Evans & Stanovich, 2013), consumers unconsciously and automatically refer to an “affective pool” of positive and negative associations when presented with a stimulus (Finucane et al., 2000; Zajonc, 1980). When augmenting textual relevance arguments with relevance-illustrating game elements, we expect that consumers' affective reactions are likely to take the form of hedonic engagement (Müller-Stewens et al., 2017; Rettie, 2001; Suh et al., 2017). Hedonic engagement reflects a situational state of mind eliciting immediate enjoyment (Agarwal & Karahanna, 2000; Hamari et al., 2016). However, contrary to prior gamification literature (Huotari & Hamari, 2017; Koivisto & Hamari, 2019), we propose that the mere addition of arbitrarily chosen game elements might not necessarily lead to hedonic engagement—as the example of Zappos from the introduction illustrates. Rather, based on emerging research (Eisingerich et al., 2019),

we propose that anticipation of hedonic engagement only emerges if game elements are tailored to the specific situation. In the case of data requests, this means that game elements need to match the textual relevance arguments in order to facilitate favorable effects on consumers' anticipation of hedonic engagement. Hedonic engagement in turn is likely to influence behavioral intentions, as extensive evidence from prior literature suggests (Hsu & Lu, 2004; Rettie, 2001; Suh et al., 2017; Webster et al., 1993).

In sum, employing data disclosure requests that facilitate textual relevance arguments with relevance-illustrating game elements should amplify consumers' willingness to enter the disclosure process through consumers' anticipation of meaningful engagement and hedonic engagement.

H2: Facilitating textual relevance arguments with relevance-illustrating game elements increases consumers' intentions to enter the data disclosure process through anticipation of a) meaningful engagement and b) hedonic engagement.

3.3 Study 1: The Base Effect – Increasing Willingness to Comply with Data Requests

Before testing our proposed dual-processing model in study 2, study 1 first tests our base assumption on the effectiveness of facilitating textual relevance arguments with relevance-illustrating game elements. Within this study, we compare common industry practice of employing textual relevance arguments without game elements with a request facilitating the textual relevance argument with relevance-illustrating game elements.

3.3.1 Design, Participants, and Procedure

We employed an online scenario experiment to investigate our base effect in a controlled setting (Aguinis & Bradley, 2014) that produces valid results related to consumers' perceptions and intentions. We randomly assigned participants to a single treatment with two conditions, for which we manipulated the data disclosure request in a fictional online fashion retail setting. Fashion online shops are ubiquitous and commonly request private data from consumers, so they provide a reasonable and realistic study setting. Based on common industry practice, we told participants that the fashion retailer required personal data to provide personalized services and style recommendations—this reflects the textual relevance argument of the data request.

In order to manipulate the relevance-illustrating game elements, we included videos previewing either a generic data request form (i.e., no game elements) or a data disclosure process, where data disclosure involved creating an avatar that mimics the participants (see Appendix Table A3.1, A3.3, Appendix Figure A3.1). We chose the creation of avatars as our manipulation of relevance-illustrating game elements because they represent game elements that facilitate consumers' understanding of the textual relevance argument: A personal avatar illustrates the collected data in a way that allows consumers to envision how the data might be used for personalization purposes (Reeves & Read, 2009). We used videos previewing the data disclosure process for two reasons. First, a dynamic visual approach helps consumers to anticipate how they it would be like to actually confront game elements, which in turn, should increase consumers' perception of the relevance-illustrating game elements as amplifiers of the request's textual relevance argument. Second, previewing videos is a realistic retailing practice. The videos were matched to participants' gender, so that female (male) participants saw a video featuring a

female (male) avatar. In the data disclosure condition without relevance-illustrating game elements, participants watched a video that detailed the procedure for filling out a form, with data tailored to either male or female characteristics (e.g., average height). Both data disclosure requests collected the same data (i.e., physical appearance, financial affairs).

We administered the questionnaire to a convenience sample of 114 students from our university ($M_{Age} = 23.11$ years, $SD_{Age} = 6.65$, 59% women). After we exposed respondents to the manipulation, they indicated their intention to enter the data disclosure process (i.e., comply with the data request). We adopted three items from Malhotra et al. (2004), using a 7-point semantic differential scale, to measure disclosure intentions. This established multi-item scale offers strong reliability and validity (for items and reliability measures see Appendix Table A3.4). Next, participants completed manipulation checks. Specifically, they indicated how relevant (“When deciding to update my profile, I could understand that the update will result in future benefits for me”) and how enjoyable (“When deciding to update my profile, I would feel that I could have fun”) they perceived the data request. Finally, participants reported their perception of the scenario’s realism. We included age and gender as a control variable into our analysis.⁵

3.3.2 Results of Study 1

Manipulation Check. Results from study 1 indicate that data requests where relevance-illustrating game elements facilitate textual relevance arguments were perceived to convey more relevance ($t(112) = -2.03$, $p = .045$, $M_{NoGame} = 3.36$; $M_{Relevance-illustratingGame} = 4.06$) and are more enjoyable ($t(86.68) = -4.48$, $p < .01$, $M_{NoGame} = 1.87$; $M_{Relevance-illustratingGame} = 3.34$) compared to common industry practice,

⁵ Results of control variables throughout the paper are discussed only when they are significant.

where only textual relevance arguments are used without any game elements.

Participants perceived both scenarios as similarly realistic ($t(112) = .022, p = .98$,

$M_{NoGame} = 3.34; M_{Relevance-illustratingGame} = 3.34$).

Intention to Enter. An ANCOVA on consumers' intention to enter the disclosure process revealed a marginally significant effect of facilitating textual relevance arguments with relevance-illustrating game elements ($F(1, 110) = 3.63, p = .06, \eta_p^2 = .04$). Participants reported less favorable disclosure intentions if the data request included no game elements ($M_{NoGame} = 2.28$) compared to when it included relevance-illustrating game elements ($M_{Relevance-illustratingGame} = 2.96$). This finding confirms hypothesis H1 pertaining to our proposed base effect.

3.3.3 Discussion of Study 1

Study 1 confirms our hypothesis H1 about the favorable effect of confronting consumers with a data request where textual relevance arguments are facilitated through game elements that are tailored to the textual relevance arguments. If a data request includes a preview of a disclosure process employing relevance-illustrating game elements, consumers report higher intentions to enter the previewed process. These results constitute support for our proposed approach to design data disclosure requests to convey the purpose of data disclosure through both textual arguments and relevance- illustrating game elements.

3.4 Study 2: Facilitating Textual Relevance Arguments with Relevance-illustrating Game Elements

Within our first study, we investigated the base effect pertaining to the effectiveness of supporting textual relevance arguments with relevance- illustrating game elements. With study 2 we pursue two goals: First, we examine the two means to facilitate consumers' appreciation of the relevance of data disclosure by

manipulating textual relevance arguments and relevance- illustrating game elements separately. By doing so, we underpin our argument that the usage of relevance- illustrating game elements without the corresponding textual relevance arguments does not result in favorable effects. Second, we investigate the mechanisms underlying the favorable effect on disclosure intentions through consumers' anticipation of meaningful and hedonic engagement according to a dual-processing model.

3.4.1 Design, Participants, and Procedure

We employed a 2 (no textual relevance arguments vs. textual relevance arguments) x 2 (no game elements vs. relevance-illustrating game elements) experimental design. Again, we manipulated the data disclosure request in a fictional online fashion retail setting. In order to manipulate the existence of textual relevance arguments in the disclosure request, we randomly assigned participants to either a condition where they were not given any information on how the retailer would use the disclosed data in the future (i.e., "We would like to update our database and need some additional information. Please fill out the following survey."), or we told them that the data would be used for personalization purposes (i.e., "We would like you to benefit from personalized product suggestions and search results. For this, we want to get to know you better."). We manipulated the game elements as in study 1: We presented participants with either a short video demonstrating a generic data request form (i.e., preview of a non-gamified process) or a request featuring a preview of a data disclosure process, where data disclosure involved creating an avatar (i.e., relevance-illustrating game elements) (see Appendix Table A3.1, A3.3, Appendix Figure A3.1).

After we exposed respondents to the manipulations, they indicated their intention to enter the data disclosure process as in study 1 and answered questions

related to the process variables from our conceptual model. We adopted five items from Suh et al. (2017) to measure anticipation of meaningful engagement and five items from Voss et al. (2003) to measure anticipation of hedonic engagement. Both constructs were measured on 7-point Likert scales. Next, we included manipulation checks. Those differed slightly from the ones we used in study 1 in order to better capture the separate components of our 2 x 2 manipulation. Specifically, participants indicated how gamified (“The data request included gameful elements.”) and how relevant (“I could understand from the data request how I could benefit from disclosure.”) they perceived the data disclosure request to be (7-point Likert scales). Finally, participants reported their perception of the scenario’s realism and socio-demographic aspects.⁶ Appendix Table A3.4 provides a summary of the study’s items and reliability measures.

We recruited participants from a professional panel provider. 330 participants representative of German online shoppers completed the questionnaire. We excluded 15 participants due to quality issues (i.e., systematic response patterns), resulting in a final sample of 315 participants ($M_{Age} = 42.54$ years, $SD_{Age} = 15.14$, 59.5% women).

3.4.2 Results of Study 2

Manipulation Checks. Running our manipulation check, we find that our manipulation of relevance ($F(3,311) = 17.94, p < .01, M_{NoRelevance-NoGame} = 2.88, M_{NoRelevance-Game} = 3.27, M_{Relevance-NoGame} = 4.01, M_{Relevance-Game} = 4.70$) as well as game elements ($F(3,311) = 70.93, p < .01, M_{NoRelevance-NoGame} = 2.81, M_{Relevance-NoGame} = 3.20, M_{NoRelevance-Game} = 5.16, M_{Relevance-Game} = 5.44$) worked as intended. Moreover, participants perceived all conditions as similarly realistic ($F(3,311) = 1.52, p = .21,$

⁶ Appendix Table A3.5 provides descriptive statistics and correlations for study variables.

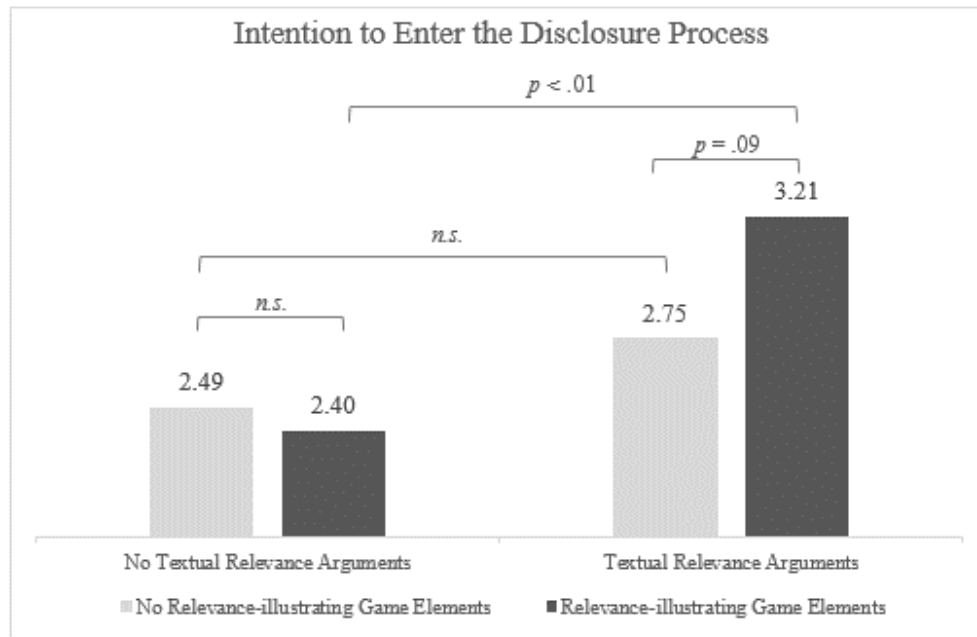
$M_{NoRelevance-NoGame} = 3.28$, $M_{NoRelevance-Game} = 3.27$, $M_{Relevance-NoGame} = 3.48$, $M_{Relevance-Game} = 3.66$).

Intention to Enter. An ANCOVA on consumers' intention to enter the disclosure process revealed a significant main effect of textual relevance arguments ($M_{NoRelevance} = 2.44$ vs. $M_{Relevance} = 2.99$; $F(1, 309) = 7.27$, $p < .01$, $\eta_p^2 = .02$), while the main effect of game elements ($M_{NoGame} = 2.63$ vs. $M_{Game} = 2.80$; $F(1, 309) = .87$, $p = .35$, $\eta_p^2 = .003$) and the interaction of the two components ($F(1, 309) = 1.99$, $p = .16$, $\eta_p^2 = .01$) were both nonsignificant.

The Base Effect. In order to investigate whether this study supports H1, we compare disclosure means from the conditions which included textual relevance arguments: In line with the results from study 1, we find that participants reported amplified disclosure intentions if the textual relevance arguments were facilitated through relevance-illustrating game elements ($M_{Relevance-Game} = 3.21$) compared to when there were no game elements ($M_{Relevance-NoGame} = 2.75$, $p = .09$). On the other hand, if there were no textual relevance arguments in the data request, the addition of game elements did not trigger more favorable disclosure intentions ($M_{NoRelevance-NoGame} = 2.49$ vs. $M_{NoRelevance-Game} = 2.40$; $p = .74$), as figure 3.2 depicts.

Moderated Mediation Model. To investigate the underlying mechanisms through a cognitive and an affective processing route, we calculated a moderated mediation model using the PROCESS macro for SPSS (Hayes, 2018; Model 8; 5,000 bootstrapping samples, 95% bias-corrected confidence interval (CI)).⁷ We consider age and gender as covariates because prior literature found those factors to influence data disclosure behavior (Smith et al., 2011).

⁷ Within all studies, we calculated mediation and moderation models with standardized construct variables; hence, reported effect sizes are standardized beta values.

Figure 3.2. Study 2 – Consumers’ Intention to Enter the Disclosure Process.

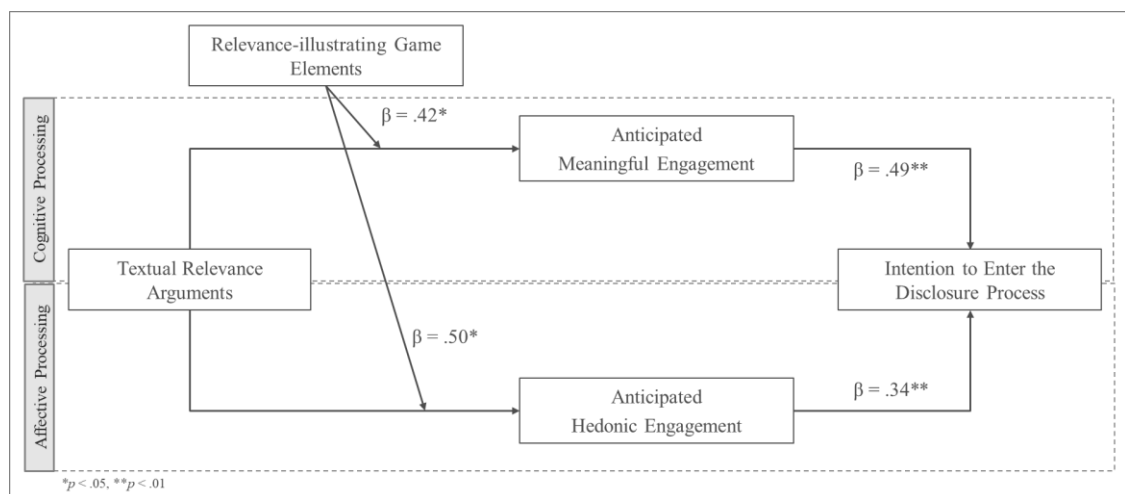
We first examined the effect of textual relevance arguments \times relevance-illustrating game elements on consumers’ willingness to enter the disclosure process. Results reveals a nonsignificant interaction ($\beta = -.07$, $t(307) = -.49$, $p = .63$), which is unproblematic for our hypotheses, as it is no precondition for a mediating effect (Zhao et al., 2010). Thus, we continue to follow Zhao et al. (2010) in an effort to investigate our proposed mediation through meaningful and hedonic engagement, which we detail in the following.

Cognitive Processing Route: Mediation through Anticipation of Meaningful Engagement. Investigating the mediating route through consumers’ anticipation of meaningful engagement, we find that textual relevance arguments increased consumers’ anticipation of meaningful engagement ($\beta = .42$, $t(311) = 3.93$, $p < .01$). When enhancing these textual relevance arguments with relevance-illustrating game elements, consumers’ anticipation of meaningful engagement can be further facilitated ($\beta = .42$, $t(309) = 2.02$, $p = .04$). Meaningful engagement in turn increases disclosure intentions ($\beta = .49$, $t(307) = 9.58$, $p < .01$). Conditional effects show that consumers’ anticipation of meaningful engagement mediates only if the textual

relevance arguments are augmented with relevance-illustrating game elements ($a \times b = .31$, 95% CI = [.155, .474]); it does not do so if there are no relevance-illustrating game elements ($a \times b = .10$, 95% CI = [-.039, .263]). These findings support hypotheses H2a.

Affective Processing Route: Mediation through Anticipation of Hedonic Engagement. Investigating the second mediating route, results reveal the effectiveness of textual relevance arguments on consumers’ anticipation of hedonic engagement ($\beta = .38$, $t(311) = 3.53$, $p < .01$). Furthermore, we find support for H2b: Augmenting textual relevance arguments with relevance-illustrating game elements facilitates consumers’ anticipation of hedonic engagement ($\beta = .50$, $t(309) = 2.36$, $p = .02$) as we depict in figure 3.3. Hedonic engagement, in turn, fosters disclosure intentions ($\beta = .34$, $t(307) = 6.67$, $p < .01$). Conditional effects reveal that consumers’ anticipation of hedonic engagement mediates only if textual relevance arguments are accompanied by relevance-illustrating game elements ($a \times b = .21$, 95% CI = [.098, .350]); it does not do so if there are no relevance-illustrating game elements ($a \times b = .04$, 95% CI = [-.049, .149]).

Figure 3.3. Study 2 – Anticipation of Meaningful and Hedonic Engagement.



3.4.3 Discussion of Study 2

Results from study 2 replicate our base effect from study 1: adding relevance-illustrating game elements to a data request which already employs textual relevance arguments, increases consumers' willingness to enter the data disclosure process. Further, study 2 uncovers the mechanisms underlying this favorable effect. We find that both meaningful and hedonic engagement only mediate the favorable effect of our proposed approach on consumers' disclosure intentions if textual relevance arguments are facilitated through relevance-illustrating game elements. Thus, employing a gamified approach without conveying relevance to consumers through corresponding textual arguments will not increase consumers' willingness to enter the disclosure process. On the other hand, if a data request comprises textual relevance arguments, the favorable effect of those arguments on consumers' anticipation of meaningful and hedonic engagement can be amplified through relevance-facilitating game elements. These findings support our hypotheses on consumers' processing of a data request where textual relevance arguments are facilitated with relevance-illustrating game elements through both cognitive and affective processing routes.

3.5 Study 3: Employing Hedonic Game Elements vs. Relevance-illustrating Game Elements

Within our previous studies, we included relevance-illustrating game elements to facilitate textual relevance arguments from the data disclosure request. Study 3 now seeks to underpin the importance of tailoring game elements to the textual relevance arguments in order to effectively illustrate the purpose of data disclosure. Specifically, building on our knowledge pertaining to the fact that game elements need to be included in a data request to facilitate textual relevance

arguments, this study now tests how these game elements need to be designed to facilitate textual relevance arguments. To investigate relevance-illustrating game elements, we thus far chose avatars as a form of tailored game elements in the fashion context. In study 3, we compare this relevance-illustrating game element with a purely hedonic gamification approach, where motivational affordances are not tailored to the relevance argument and merely serve the purpose of entertainment.

3.5.1 Design, Participants, and Procedure

We employed a single factor design manipulating game elements such that one group of participants was confronted with relevance-illustrating game elements as in the previous studies (i.e., avatar) and the other group was confronted with purely hedonic game elements not tailored to the textual relevance argument (i.e., icons, visually appealing buttons, and sliders; Bailey et al., 2015). As in the previous studies, the textual relevance argument in both conditions highlighted the need to comply with the data request for future personalization benefits. Measures of process variables were the same as in the previous studies (see Appendix Table A3.4). Again, we considered age and gender as covariates. We recruited participants representative of German online shoppers from a professional panel provider as in study 2. 220 participants completed the questionnaire. Excluding 11 participants due to quality issues (e.g., systematic response patterns) resulted in a final sample of 209 participants ($M_{Age} = 40.45$ years, $SD_{Age} = 15.54$, 53.1% women).

3.5.2 Results of Study 3

Intention to Enter. An ANCOVA on consumers' intention to enter the disclosure process revealed a marginally significant effect of relevance-illustrating game elements ($M_{HedonicGame} = 2.91$ vs. $M_{Relevance-illustratingGame} = 3.41$; $F(1, 205) = 3.39$, $p = .07$; $\eta_p^2 = .02$). Participants reported less favorable disclosure intentions if the

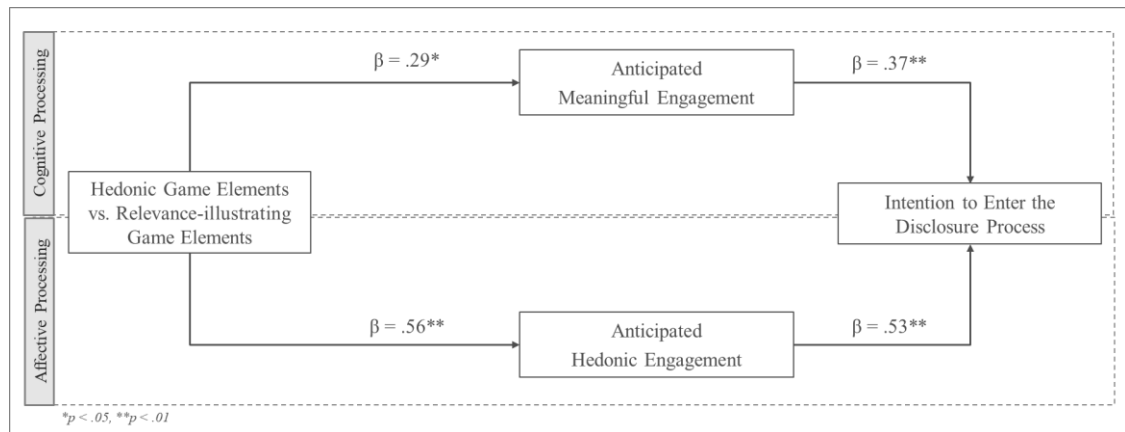
data request comprised hedonic vs. relevance-illustrating game elements. Age ($F(1, 205) = 10.61, p < .01; \eta_p^2 = .05$) was a significant covariate.

Mediation Analysis. We conducted serial mediation analyses (Hayes, 2018, Model 4; 5,000 bootstrapping samples, 95% bias-corrected CI; covariates: age and gender), estimating the indirect effects of hedonic game elements vs. relevance-illustrating game elements through consumers' anticipation of meaningful and hedonic engagement on their intention to enter the disclosure process.

Cognitive Processing through Consumers' Anticipation of Meaningful Engagement. The results revealed that relevance-illustrating game elements help consumers to better anticipate meaningful engagement as compared to hedonic game elements ($\beta = .29, t(205) = 2.09, p = .04$). Meaningful engagement in turn increases consumers' intention to enter the data disclosure process ($\beta = .37, t(203) = 6.24, p < .01; a \times b = .11, 95\% \text{ CI} = [.006, .226]$).

Affective Processing through Consumers' Anticipation of Hedonic Engagement. Relevance-illustrating game elements help consumers to better anticipate hedonic engagement as compared to purely hedonic game elements ($\beta = .56, t(205) = 4.12, p < .01$). Higher anticipation of hedonic engagement in turn increases consumers' intentions to enter the data disclosure process ($\beta = .53, t(203) = 8.84, p < .01; a \times b = .30, 95\% \text{ CI} = [.144, .471]$). Figure 3.4 summarizes the mediation model.

Figure 3.4. Study 3, Hedonic vs. Relevance-illustrating Game Elements.



3.5.3 Discussion of Study 3

Study 3 reveals the importance of tailoring relevance-illustrating game elements to textual relevance arguments. Results underpin our proposed approach of using avatars to facilitate the textual relevance argument of personalization in the fashion context. Using relevance-illustrating avatars not only helps consumers to envision the future benefits of the data disclosure but is also perceived to be more hedonically engaging. Other contexts and other purposes of data disclosure need to tailor game elements to fit their specific relevance arguments respectively in order to create effective relevance-illustrating game elements. Next, study 4 tests consumers’ trust as a contingency factor for the effectiveness of employing relevance-illustrating game elements.

3.6 Study 4: Trust as a Contingency Factor

Our investigations so far consistently underpin our argument pertaining to the facilitating effect of relevance-illustrating game elements to amplify consumers’ appreciation of textual relevance arguments. However, one crucial contextual variable from the privacy domain, which we did not consider thus far, is consumers’ trust in the retailer (Benedicktus et al., 2010; Bleier & Eisenbeiss, 2015; Culnan & Armstrong, 1999; Dinev & Hart, 2006; Grosso et al., 2020). Retailers facing

customers with lower levels of trust confront the particularly tough challenge of encouraging consumers to comply with their data disclosure requests. Building on our findings from study 3, where results highlight the need to employ tailored, relevance-illustrating game elements instead of purely hedonic game elements, we now investigate trust as a contingency factor for this effect within study 4. We argue that our proposed approach of facilitating textual relevance arguments with relevance-illustrating game elements might help to compensate for consumers' reluctance to disclose data to retailers in which they have low trust (because of, e.g., negative experiences, no prior experiences, negative WOM, etc.). In comparison, retailers facing customers with high trust levels will already benefit from the favorable relationship; hence, the facilitating effects of relevance-illustrating game elements (vs. purely hedonic game elements) will be less pronounced.

3.6.1 Design, Participants, and Procedure

We employed a 2 (hedonic game elements vs. relevance-illustrating game elements) x 2 (low trust level vs. high trust level) experimental design. We manipulated the level of trust by including a short introduction prior to the data request. For this, we told one group that they were customers of a well-known online fashion retailer and that their prior experiences with this retailer were positive, while we informed the other group that they had had a couple of negative experiences with a new retailer (see Appendix Table A3.1, A3.2, A3.3, Appendix Figure A3.1). Both conditions were presented with a data request employing textual relevance arguments. Our manipulation of game elements as well as the measures and procedure were the same as in study 3. Additionally, we included four items to measure perceived trust (Bobinski, 1996; for items and reliability measures see Appendix Table A3.4). As in the previous studies, we included age and gender as control variables. In this study, we also controlled for perceived risks and benefits of

data disclosure, because our manipulation of trust might have induced unintentional interferences with consumers' perceptions of the risks and benefits of data disclosure. As in the previous studies, we recruited participants representative of German online shoppers from a professional panel provider. 330 participants completed the questionnaire. Excluding 10 participants due to quality issues (e.g., systematic response patterns) resulted in a final sample of 320 participants ($M_{Age} = 41.75$ years, $SD_{Age} = 13.75$, 53.4% women).

3.6.2 Results of Study 4

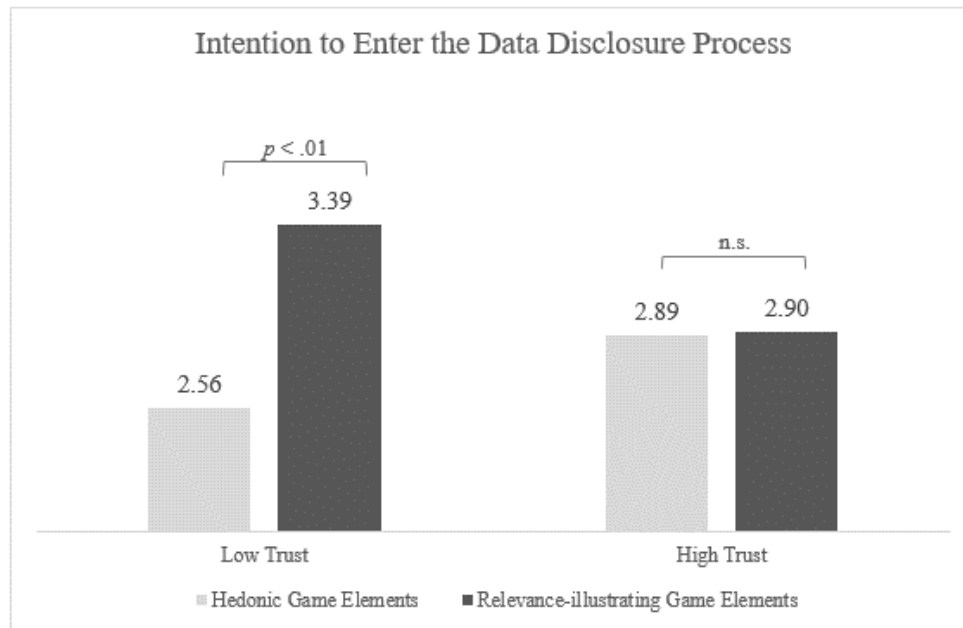
Manipulation Check. An ANOVA revealed that our manipulation of trust performed as intended ($F(3,316) = 37.03$, $p < .01$) such that participants in the low trust condition reported less trust ($M_{LowTrust-HedonicGame} = 3.21$; $M_{LowTrust-Relevance-illustratingGame} = 2.77$) compared to participants in the high trust condition ($M_{HighTrust-HedonicGame} = 4.29$, $M_{HighTrust-Relevance-illustratingGame} = 4.79$).

Intention to Enter. An ANCOVA on consumers' intention to enter the disclosure process as a function of the level of trust, game elements, and their interaction, revealed a significant interaction ($F(1, 312) = 5.36$, $p = .02$, $\eta_p^2 = .02$). The analysis also revealed a significant main effect of relevance-illustrating game elements ($F(1, 312) = 5.93$, $p = .02$, $\eta_p^2 = .02$), while the main effect of trust level was nonsignificant ($F(1, 312) = .19$, $p = .66$, $\eta_p^2 = .00$). Moreover, we find significant effects of the covariates risk perceptions ($F(1, 312) = 63.28$, $p < .01$, $\eta_p^2 = .17$), and benefit perceptions ($F(1, 312) = 84.48$, $p < .01$, $\eta_p^2 = .21$).

Moderation Analysis. We conducted a moderation analyses (Hayes, 2018) to further explore the significant interaction of level of trust and relevance-illustrating game elements. Conditional effects show that there is no difference between purely hedonic game elements vs. relevance-illustrating game elements for the high trust setting ($\beta = .01$, $t(312) = .08$, $p = .94$). In contrast, relevance-illustrating game

elements compared to purely hedonic game elements significantly increased disclosure intentions in the low trust condition ($\beta = .43$, $t(312) = 3.36$, $p < .01$), as figure 3.5 depicts.

Figure 3.5. *Study 4, Hedonic vs. Relevance-illustrating Game Elements at Low vs. High Trust Levels.*



3.6.3 Discussion of Study 4.

While study 3 found relevance-illustrating game elements to elicit more favorable outcomes compared to purely hedonic game elements, study 4 shows that this is only the case for retailers facing customers with low levels of trust. Specifically, results uncover that data disclosure requests, in which textual relevance arguments are facilitated with relevance-illustrating game elements are an effective strategy to overcome consumers' reluctance to disclose personal details to retailers with whom they do not have a trustworthy relationship. In comparison, retailers facing customers with high levels of trust do not need to put additional effort into convincing consumers to comply with their request. Interestingly, we found that consumers' intentions to comply with a request comprising relevance-illustrating game elements are higher in a low trust setting compared to a corresponding high

trust setting. One potential explanation for this overly positive effect might be that by amplifying the effectiveness of textual relevance arguments with relevance-illustrating game elements, retailers exceed even the generally positive effect of trust. Further research into this effect would offer valuable insights. reviewer.

3.7 General Discussion

With this article, we introduce a new means to encourage consumers to comply with data disclosure requests. By using relevance-illustrating game elements to facilitate the effectiveness of textual relevance arguments, we increase consumers' acceptance of, and participation in, retailers' data collection processes. We also explore the underlying psychological mechanisms via two routes by reconciling these routes with dual-processing models of decision-making. Furthermore, we highlight the need to tailor game elements to textual relevance arguments, thus facilitating consumers' appreciation of future data disclosure benefits. Finally, we investigate the role of trust as a contingency factor and find support for the importance of employing relevance-illustrating game elements to convince consumers with low trust levels to comply with data requests, whereas consumers with high trust levels already show favorable, trust-driven behavior.

3.7.1 Theoretical Contributions

This study is the first to introduce data requests as a new means to encourage consumers to engage in data disclosure by combining approaches from privacy and gamification literature. Whereas retailing literature and privacy literature often focus on increasing consumers data disclosure behavior during a data disclosure process, we argue that is in fact a crucial first step, to facilitate consumers' willingness to enter a data disclosure process. Specifically, we contribute to existing research by arguing that convincing consumers to enter a data disclosure process is the crucial

bottleneck—once entered, consumers are more likely to also finish the data disclosure process. Against this background, we advocate for the need to address this initial hurdle separately from privacy-related disclosure behavior in general. So far, privacy research mainly has focused on investigating risks and benefits related to consumers' willingness to disclose data, without differentiating between consumers' willingness to enter the disclosure process and their willingness to disclose after entering the process (Smith et al., 2011). While research offers extensive insights into consumers' privacy-related decision-making, we argue that investigated aspects such as privacy protection seals or rewarding coupons (Hui et al., 2007; Pan & Zinkhan, 2006; Xu et al., 2009) constitute suboptimal forms of leverage. Such personalization-unrelated, situational cues might lose effectiveness quickly (Acquisti et al., 2013) and fail to address consumers' demands for long-term benefits related to the disclosed data (Data & Marketing Association, 2018). To overcome those limitations, we suggest that data requests should include textual relevance arguments and facilitating relevance-illustrating game elements to help consumers envision and appreciate the direct benefits of data disclosure.

Our proposed approach also contributes to retailing literature by extending the literature's understanding of consumers' acceptance of direct marketing approaches, such as personalization and online targeting, in the context of data disclosure (Goldfarb & Tucker, 2011; Milne & Gordon, 1993; Schumann et al., 2014). While all retailers can benefit from our proposed approach, retailers facing low trust consumers are likely to benefit the most when textual relevance arguments are facilitated through relevance-illustrating game elements: Retailers facing customers who they have (not yet) established a trustworthy relationship with, or where prior service failures have damaged the relationship, need to put extra effort into convincing consumers of the benefits resulting from data disclosure. Hence,

these retailers highly profit from facilitating textual relevance arguments with relevance-illustrating game elements. On the other hand, high trust customers are likely to engage in trust-driven, favorable behavior such that additional game elements do not trigger amplifying effects.

Third, by integrating textual relevance arguments and affective easily processable game elements (i.e., relevance-illustrating game elements) to lever disclosure intentions, we advance research on the effectiveness of relevance arguments (Aguirre et al., 2016; Bleier & Eisenbeiss, 2015; Schumann et al., 2014), as well as privacy literature that advocates for the importance of affective processing (Alashoor et al., 2018; Dinev et al., 2015; Gerlach et al., 2019; Kehr et al., 2015; Li et al., 2011; Wakefield, 2013). We argue that facilitating textual relevance arguments with relevance-illustrating game elements increases consumers' intention to comply with a data request by triggering both cognitive and affective processing routes. This is in line with dual-processing models of decision-making (Epstein, 1994; Evans & Stanovich, 2013): On the cognitive processing route, consumers who are confronted with a data request, where textual relevance arguments are facilitated through game elements, are likely to thoroughly reflect on the objective benefits of disclosure such that they can anticipate meaningful engagement. On the affective processing route, consumers also more easily anticipate hedonic engagement reflecting their appreciation of the relevance-illustrating game elements as entertaining. This dual processing perspective on consumers' privacy-related decision-making responds to a call by Dinev et al. (2015) for empirical research on high-effort (i.e., cognitive) and low-effort (i.e., affective) processing in the privacy domain. As such, we enrich emerging research that highlights the importance of dual processing—and affective reactions in particular—in privacy-related decision-making (e.g., Gerlach et al., 2019; Kehr et al., 2015; Li et al., 2011). Advancing our proposed dual-processing

perspective, future research could provide further evidence on consumers' tendencies to inform their privacy-related decision-making with contextual cues. Findings could help design privacy-related situations to yield favorable outcomes for both firms and consumers.

Finally, our results contribute to existing literature in the gamification domain (Csikszentmihalyi, 1990; Hamari et al., 2016; Müller-Stewens et al., 2017; Rettie, 2001) by advancing the literature's understanding of the interaction of meaningful and hedonic engagement. Specifically, our results disagree with the widely accepted focus on hedonic engagement in order to elicit favorable behavioral outcomes (e.g., Berger et al., 2018; Müller-Stewens et al., 2017). We show that the mere addition of game elements does not result in more favorable behavioral intentions: Results reveal that higher disclosure intentions only emerge if game elements are accompanied by textual relevance arguments which they are tailored to. That is, we find that it is important to a) provide textual relevance arguments, which put the game elements into perspective and b) tailor the game elements to the corresponding textual arguments in order to allow consumers to anticipate both hedonic and meaningful engagement (Deterding, 2012; Eisingerich et al., 2019). As such, we respond to calls for more research into the role of meaningful engagement and the interaction of hedonic and meaningful engagement (Eisingerich et al., 2019; Liu et al., 2017; Mekler et al., 2013; Nicholson, 2015; Suh et al., 2017).

3.7.2 Managerial Implications

Our results also have important implications for retail managers. Addressing retailers' challenge to gather and exploit consumer data to uphold competitive advantages, we argue that the crucial bottleneck is to convince consumers to enter data disclosure processes. Once consumers have entered, they are more likely to also finish the data disclosure process. Thus, we advocate for the need to concentrate on

designing data requests and propose an effective lever to overcome consumers' negative attitudes towards disclosing personal data (Culnan & Armstrong, 1999): Instead of offering unrelated cues (i.e., additional incentives such as coupons), retailers should actively counteract consumers' doubts about whether they would actually benefit from disclosure in the long-term (i.e., through personalization). To do so, retailers should design data requests in such a way, that textual relevance arguments help consumers to understand the relevance of their data disclosure decision—i.e., how the requested data leads to future personalization benefits. At the same time, the integration of game elements (i.e., avatars, icons, or badges) that are tailored to the textual relevance arguments, allow consumers to envision the direct benefits and the entertaining experience resulting from the decision to enter the data disclosure process. Thus, retailers should employ a data request that uses textual relevance arguments facilitated through affective, easily processable—relevance-illustrating—game elements to convince consumers of the value of complying with the data request. However, we caution retailers not to employ purely hedonic game elements because it can lead to unfavorable results, as in the example of Zappos (eLearning Industry, 2017). To achieve positive outcomes, game elements need to be directly linked to the requested data: In the fashion retailing context, for example, the creation of a personal avatar represents a suitable leverage to facilitate consumers' decision-making. Creating an avatar is not only enjoyable but also summarizes the collected data in a way that provides consumers with the opportunity to envision future personalization benefits.

Retailers facing customers with lower levels of trust (e.g., due to prior service failure, no established customer relationships, or negative WOM) can especially benefit from our proposed approach. While high trust customers are likely to engage in data disclosure processes because they trust retailers to uphold their promise of

personalization benefits, low trust customers' skepticism about future personalization benefits needs to be counteracted. Retailers facing customers with low trust levels can more easily convince them of the benefits by including relevance-illustrating game elements in their request. These game elements help low trust customers to better envision the relevance of data disclosure and facilitate their understanding as they are more affective, easily processable, and entertaining.

Finally, we suggest that the scope of this approach can be enlarged in two ways: First, retailers could additionally ask for data on consumer preferences. By expressing preferences on favorite colors or cuts in the fashion retailing context, consumers could further benefit from personalized product suggestions. Retailers, in turn, would benefit from gaining more in-depth insights for segmentation and product innovation efforts. Second, our proposed approach can be adapted to different contexts, e.g., the furniture or horticulture industry. Therefore, relevance-illustrating game elements need to be tailored to the specific context to allow consumers to envision how they could benefit from personalized product suggestions and search results. That is, instead of creating a personal avatar, consumers might virtually create their room or garden by disclosing data. For example, in the context of horticulture, consumers could disclose how big their garden was, what kind of plants they prefer, and how much budget they have. Consumers would disclose these data by creating a digital version of their garden and hence, could more easily understand how they might benefit from future product suggestions.

3.7.3 Limitations and Further Research

The limitations of this study offer opportunities for further research. First, we investigated data requests that included various game elements (e.g., avatars, direct feedback, visually appealing buttons, icons, and curiosity; Deterding et al., 2011). While study 3 sheds light on the importance of tailoring game elements to illustrate

the relevance of data disclosure decisions (i.e., game elements such as avatar, sliders, visually appealing buttons, etc. that summarize the requested data), future research might wish to investigate the influence of (other) motivational affordances separately. For example, curiosity functions as a hedonically beneficial motivator in the marketing context (Ruan et al., 2018), constituting an interesting research object. Investigating curiosity could account for the fact that consumers are often intrigued to engage in novel situations (Venkatraman, 1991), hence adding another perspective on our proposed effectiveness of game elements through hedonic and meaningful engagement.

Second, within all of our studies, we manipulated textual relevance arguments in an effort to convey the relevance of data disclosure to consumers. While manipulation checks underpin our argument that textual relevance arguments help consumers to appreciate data disclosure benefits (i.e., future personalization), the manipulation might also have increased consumers' awareness of the retailer's benefit. That is, suspicious consumers might think that their disclosed data could be used to request higher prices for personalized offers. Further research could investigate this trade-off between the benefits and potential risks. In this context, it might also be interesting to investigate other aspects related to consumers' risk and benefit perceptions: e.g., do consumers account for the process effort of creating an avatar vs. simply filling out a form—or are consumers too focused on the positive aspects and overlook the downsides?

Third, we investigated data disclosure requests in an online fashion retailing context. We choose this context for three reasons: First, the retail segment holds the largest share in the gamification market (Cole Reports, 2020). Second, the context of fashion retailing highly relies on consumer data to personalize offers to address industry challenges (Infinity Research, 2019; Women's Wear Daily, 2019). Thus, it

constitutes a highly realistic setting in which consumers encounter data requests regularly (Schumann et al., 2014). Third, as we propose a new approach, our primary goal was to understand the constituting components and how the components interact without exogenous influences aroused by different contexts. Further research might want to explore data disclosure requests that include textual relevance arguments and facilitating relevance-illustrating game elements in other contexts. Are there contexts in which consumers would not comply with such a data request—e.g., because it seems unfitting to employ game elements or because the contextual sensitivity of the requested data might be perceived as too high?

Finally, continued research might investigate the next step of our proposed approach. While we investigated data disclosure requests as a means to increase consumers' intentions to enter the disclosure process, additional studies could examine how consumers behave during the previewed data disclosure process, after they have entered. In this context, our paper's findings regarding trust as a contingency factor might be further advanced: Could it be that while relevance-illustrating game elements increase consumers' willingness to enter a data disclosure process in low trust settings, consumers' behavior during the actual disclosure process yields less favorable outcomes? Consumers with low trust levels might disclose less data or incorrect data after entering because of their generally low levels of trust. Or would consumers—regardless of trust levels—answer more truthfully because they understand that genuine answers will result in greater personalization benefits?

3.8 Conclusion

To resolve the increasing tension between retailers' need for consumer data and consumers' reluctance to enter data disclosure processes, we propose a data

disclosure request that facilitates textual relevance arguments with relevance-illustrating game elements as a means to encourage consumers to comply with data requests. We find that this appeal increases consumers' intentions to enter the data disclosure process through two mediation routes: (1) consumers' anticipation of meaningful engagement, reflecting cognitive processing, and (2) consumers' anticipation of hedonic engagement, reflecting affective processing. When implementing relevance-illustrating game elements into data disclosure requests, it is crucial to tailor them to the actual relevance of data disclosure (e.g., an avatar to facilitate personalization). A sophisticated use of relevance-illustrating game elements that facilitate textual relevance arguments is especially worthwhile for retailers facing customers with low trust levels.

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3.10 Appendices

Table A3.1. *Data Request: Textual (Relevance) Arguments.*

No Textual Relevance Argument <i>Study 2</i>	Textual Relevance Argument <i>Study 1, Study 2. Study 3, Study 4</i>
<p>Please fill out the following survey!</p> <p>We would like to update our customer database and need some additional information.</p> <p>Fill out the following survey: Please provide us with some additional information regarding your looks and budget.</p> <p>Your information will be stored in our customer database. We need your information to keep our customer database up-to-date.</p>	<p>We would like to improve your shopping experience!</p> <p>In future, we would like you to benefit from personalized product suggestions and search results. For this, we want to get to know you better.</p> <p>Update your profile: Please provide us with some additional information regarding your looks and budget.</p> <p>Your information will be used to present you with personalized product suggestions and search results.</p>

Table A3.2. *Scenario Introduction Study 4: Trust Setting.*

Low Trust Setting <i>Study 4</i>	High Trust Setting <i>Study 4</i>
<p>Please read the following scenario carefully and then answer the questions:</p> <p>You are a registered customer of Youlando. In the past, you had some mixed experiences with the online retailer. You discovered that Youlando does not use encryption when transmitting data; thus, you are unsure whether your personal information has always been well protected. The delivery of the ordered products usually took longer than indicated and you were not always satisfied with the quality of the products. That’s why you had to return some of the ordered products. The return process then took a long time and was not easy, so you had to wait a long time for the refund.</p> <p>Despite your mixed experiences in the past and your low level of trust in the online shop, you still want to give Youlando another chance.</p> <p>The next time you visit the website of the online retailer, you are confronted with the following request:</p>	<p>Please read the following scenario carefully and then answer the questions:</p> <p>You are a registered customer of Youlando. In the past, you only had positive experiences with the online retailer. Youlando uses the latest end-to-end encryption when transmitting data; thus, you are sure that your personal information has always been well protected. You always received the ordered products in time and were satisfied with the quality of the products. You had to return some of the ordered products. The return process was always quick and easy. You have received the refund within a very short time.</p> <p>Due to your positive experiences, you have a high level of trust in the online shop and are happy to shop at Youlando again.</p> <p>The next time you visit the website of the online retailer, you are confronted with the following request:</p>

Notes: Participants were shown the data request including the relevance argument (Table A3.1 – right side) after this introduction.

Figure A3.1. Stimulus Material: Textual Relevance Arguments and Relevance-illustrating Game Elements.

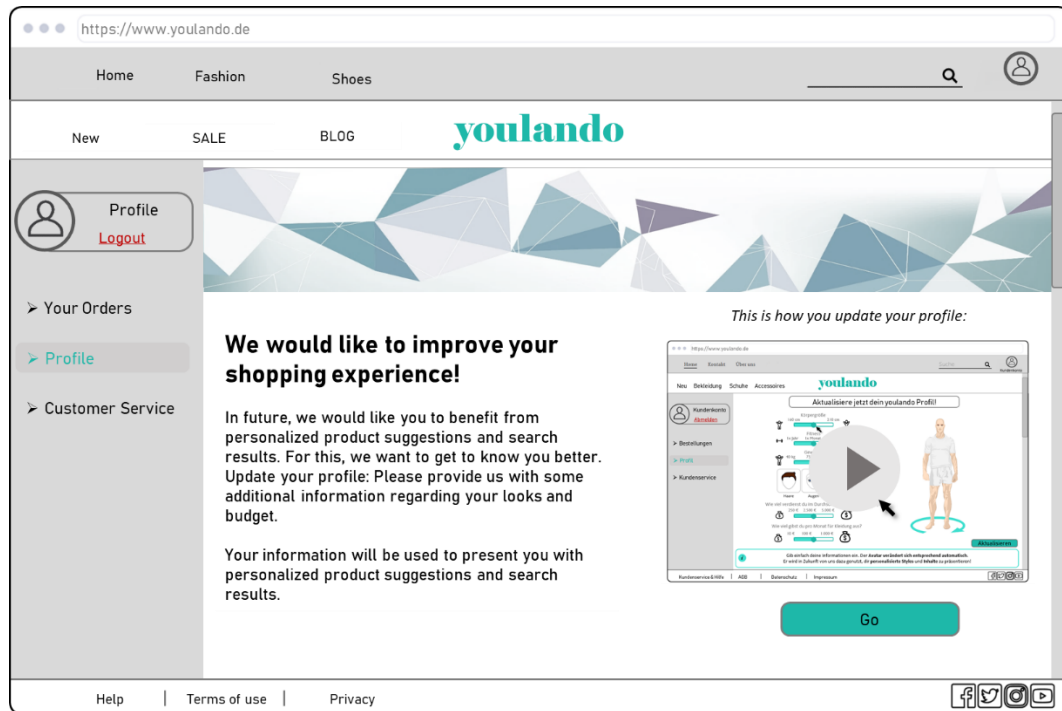


Table A3.3. Data Request: Gamification.

<p>No Game Elements <i>Study 1, Study 2</i></p>	<p>Hedonic Game Elements <i>Study 3, Study 4</i></p>	<p>Relevance-illustrating Game Elements <i>Study 1, Study 2, Study 3, Study 4</i></p>

Table A3.4. *Measurement Items and Reliability Assessment for Constructs in Studies 1–4.*

Construct	Statistics ⁸	Measurement Items ⁹
Intention to Disclose Data Malhotra, Kim, & Agarwal (2004)	$\alpha_1 = .96, CR_1 = .95,$ $AVE_1 = .85$ $\alpha_2 = .99, CR_2 = .89,$ $AVE_2 = .74$ $\alpha_3 = .98, CR_3 = .88,$ $AVE_3 = .72$ $\alpha_4 = .99, CR_4 = .86,$ $AVE_4 = .68$	Specify the extent to which you would engage in disclosing the requested personal data to Youlando. 1. Unlikely/Likely 2. Impossible/Possible 3. Unwilling/Willing
Hedonic Engagement Adapted from Voss, Spangenberg, & Grohmann (2003)	$\alpha_2 = .95, CR_2 = .91,$ $AVE_2 = .67$ $\alpha_3 = .94, CR_3 = .88,$ $AVE_3 = .60$ $\alpha_4 = .97, CR_4 = .62,$ $AVE_4 = .66$	When deciding to update my profile, I would imagine it to be ... 1. unenjoyable/enjoyable 2. unpleasant/pleasant 3. not fun/fun 4. dull/exciting 5. not delightful/delightful
Meaningful Engagement Adapted from Suh, Cheung, Ahuja, & Wagner (2017)	$\alpha_2 = .93, CR_2 = .88,$ $AVE_2 = .60$ $\alpha_3 = .94, CR_3 = .88,$ $AVE_3 = .61$ $\alpha_4 = .93, CR_4 = .85,$ $AVE_4 = .53$	When deciding to update my profile... ... I would envision how I could benefit from the update in the future. ... I would believe that the update would result in benefits for me in the future. ... I would feel that the update is important for me to benefit from personalization in the future. ... I would feel I discovered new paths to a personalized shopping experience. ... I would be aware of how to proceed to benefit from personalization in the future.
Perceived Benefits of Data Disclosure Adapted from Dinev, Xu, Smith, & Hart (2013)	$\alpha_4 = .85, CR_4 = .81,$ $AVE_4 = .59$	1. Disclosing my personal information on Youlando could help me obtain future product suggestions and content I want. 2. In the future, I could get exactly the product suggestions and content that I want from Youlando. 3. I believe that in the future I could benefit from customized product suggestions and content.
Perceived Risks of Data Disclosure Adapted from Dinev, Xu, Smith, & Hart (2013)	$\alpha_4 = .92, CR_4 = .91,$ $AVE_4 = .71$	1. In general, it would be risky to disclose personal information to Youlando when updating my profile. 2. There would be high potential for privacy loss associated with disclosing

⁸ The values in this column refer to all studies in which the measure appears; subscripts indicate the relevant study.

⁹ For all items, participants indicated their responses on 7-point Likert or semantic differential scales (1 = “strongly disagree,” and 7 = “strongly agree”).

		personal information by updating my profile on Youlando. 3. Youlando could inappropriately use my personal information that I disclose while updating my profile. 4. Providing Youlando with my personal information while updating my profile could involve many unexpected problems.
Trust	$\alpha_4 = .96$, $CR_4 = .92$, $AVE_4 = .75$	Youlando is ...
Adapted from Bobinski, Cox, & Cox (1996)		Honest/dishonest Reliable/unreliable Sincere/insincere Trustworthy/untrustworthy

Table A3.5. Study 2 – Descriptive Statistics and Correlations for Study Variables.

Variable	<i>M</i>	<i>SD</i>	1	2	3
1. Intention to Enter Disclosure Process	2.72	1.81	—		
2. Hedonic Engagement	2.92	1.54	.66	—	
3. Meaningful Engagement	2.97	1.50	.72	.68	—

4. Essay 3: “Trick or Treat!?” – A Situation-Fit-Perspective on Affect in Consumer Privacy

Johanna Zimmermann

Will be submitted to *Business Horizons* (VHB-Ranking: C)

Motivating consumers to enter a data disclosure process represents a crucial first hurdle that firms must overcome in order to obtain personal customer data. While privacy research has largely focused on cognitive cues, a growing stream of literature highlights the effectiveness of affective cues to engage consumers in data disclosure behaviors. Based on dual-processing models of decision-making, this article illustrates the importance of affective processing in consumers' privacy-related decision-making and explains how different categories of affective cues (i.e., benefit-related, environmental, and social) can (positively) elicit consumers' affect toward data requests. Adopting the Confirmation-Disconfirmation (C/D) paradigm for consumer privacy, the author conceptualizes a situation-fit perspective on the categorized affective cues and discusses examples from research and practice against this background. In doing so, this article provides a new account for understanding how consumers' initial decision to comply with a data request might influence their long-term satisfaction with disclosure decisions. This will help managers to design their data requests in an affectively appealing way without tricking their customers into behaviors they potentially regret after reflecting on them.

4.1 Introduction

"When dealing with people, remember you are not dealing with creatures of logic, but with creatures of emotion."

(Dale Carnegie, American writer and lecturer, 1888-1955)

In the modern digital world, consumers have become reluctant to share their personal data due to firms' increasing collection and use of customer data for gaining competitive advantages (Culnan & Armstrong, 1999; Martin & Palmatier, 2020). Therefore, firms must find new ways to address consumers' negative attitudes, for instance, by putting more effort into the design of their data requests. Privacy research has found that this approach of focusing on consumers' initial decision to enter a data disclosure process is particularly worthwhile pursuing because, while it is difficult to convince consumers to comply with a data request, most of them will complete the data disclosure process once they have entered it (Bidler et al., 2020; Schumann et al., 2014). To date, both research and practice have primarily relied on addressing consumers' rational decision-making to engage them in data disclosure, for example, by means of privacy notices providing data handling transparency and highlighting data control mechanisms (Gerlach et al., 2019; Martin et al., 2017; Schumann et al., 2014). However, with the growing volume and complexity of data disclosure situations, it is becoming increasingly difficult for consumers to make privacy-related decisions based solely on cognitive evaluations of data requests, as these evaluations require high processing efforts (Bleier et al., 2020; Quach et al., 2022).

To overcome this obstacle, an emerging stream of privacy literature argues that decision-making processes can be fostered by addressing the affective processing of information: According to dual-processing models of decision-making (Epstein, 1994; Finucane et al., 2000; Slovic et al., 2004), consumers do not only rely on rational, cognitive processing of information, but also on their affective reactions

when deciding (e.g., Bidler et al., 2020; Kehr et al., 2015). Affective reactions have been described as a “faint whisper of emotion” (Slovic et al., 2004; p. 312) that consumers perceive inevitably (and often unconsciously) toward a stimulus such as a data request. In everyday life, consumers often base their privacy-related decisions on their affective reactions (more or less) leaving out high-effort cognitive processing, which is why consumers’ affective processing of information represents one explanatory factor for the so-called privacy paradox (i.e., the discrepancy between their intention to disclose personal data, when explicitly asked about it, and their actual data disclosure behavior; Li et al., 2017).

Due to the importance of affect in consumers’ decision-making processes, this research focuses on affective cues in the context of consumer privacy. Affective cues are generally defined as “specific features or characteristics of a stimulus that can manifest the affective quality of the stimulus” (Zhang, 2013; p. 251). They can be viewed as signals containing affective information that trigger affective processing, which, in turn, influences consumers’ decision-making directly or indirectly by adjusting cognitive information processing (Soldat et al., 1997).

While privacy literature has already examined the effectiveness of several different affective cues in motivating consumers’ data disclosure behaviors (e.g., Angst & Agarwal, 2009; Li et al., 2011; Wakefield, 2013), no study to date offers an integrated categorization of their various properties. Further, prior research does not consider how affective cues may shape consumer expectations (e.g., how they will benefit from the data exchange) when deciding to enter a data request. Whether or not these privacy expectations are met, however, provides a critical basis for consumers’ post-data disclosure decision evaluation according to the Confirmation-Disconfirmation (C/D) paradigm (e.g., Churchill & Surprenant, 1982; Mattila & Wirtz, 2000; Oliver, 1980, 1993; Oliver & DeSarbo, 1988).

In this article, the author argues that firms should confront consumers with data requests that use *distinct affective cues* (i.e., stimuli with affective qualities) in order to explicitly target their affective reactions. Furthermore, the author proposes that there must be a *fit between the affective cues employed in a data request and the specific data disclosure situation* in order to create long-term consumer satisfaction with a disclosure decision. The situation-fit perspective is important because affective cues are likely to shape consumers' privacy expectations (e.g., Krafft et al., 2021; Swani & Milne, 2022): If the expectations triggered by affective cues in a data request do not fit the outcomes of data disclosure (i.e., the benefits they receive in exchange for personal data), consumers may feel tricked into a disclosure behavior, which firms must avoid for creating and maintaining trusting relationships with their customers.

To help research and practice understand the importance of affect in motivating data disclosure behaviors, the author first illustrates the role of affective processing of information provided in data requests based on dual-processing models of decision-making. Next, this article adopts the C/D paradigm for consumer privacy to conceptualize a situation-fit perspective on affective cues. It then identifies and categorizes affective cues (i.e., benefit-related, environmental, and social) from privacy literature. Based on the conceptualized situation-fit perspective and examples from literature and practice, a discussion of how the intentional design of affective cues, especially of those related to the benefits of data disclosure, influences the evaluation of decision outcomes allows propositions to be derived for each category of cues as well as for their interactive effects.

From an academic perspective, this article contributes to privacy literature that focuses on dual-processing models of decision-making by emphasizing the importance of eliciting affective reactions through a variety of cues (e.g., Aiello et

al., 2020; Bidler, 2019; Gerlach et al., 2019; Wakefield, 2013). Further, it contributes to literature viewing the initial decision to enter a data disclosure process as a critical bottleneck in consumer privacy by focusing on different categories of affective cues to encourage data disclosure behaviors (Bidler et al., 2020; Schumann et al., 2014). Finally, this article complements research on consumer expectations when disclosing personal data by discussing affect-driven decision-making and its long-term consequences (Dinev et al., 2015; Krafft et al., 2021; Swani & Milne, 2022). From a managerial perspective, the findings provide firms with practical recommendations on how to design data requests, while also raising awareness of the risks of prioritizing short-term success over long-term consumer satisfaction by introducing a situation-fit perspective on affective cues. Customer data disclosure satisfaction is becoming increasingly important and has implications beyond privacy because the compliance with a data request can be understood as consumer's general consent to start and continue an interaction with a firm.

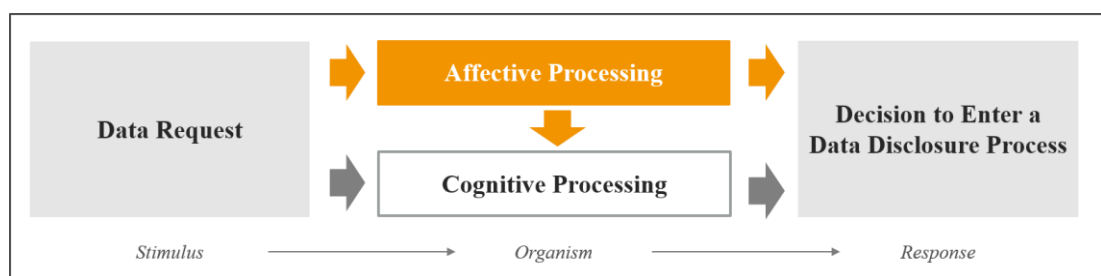
4.2 Theoretical Background and Conceptualization

4.2.1 The Importance of Affect in Consumers' Dual-Processing Models of Decision-Making

Dual-processing models of decision-making propose that consumers process decision-making tasks through two parallel processing routes (Epstein, 1994; Finucane et al., 2000; Shiv & Fedorikhin, 1999). On the one hand, consumers show an immediate and automatic affective reaction (i.e., affective processing) that helps to consciously or unconsciously characterize a stimulus in terms of valence (“good” or “bad”) as well as in terms of intensity. It is important to note that this automatic affective reaction is inevitable as Zajonc (1980) illustrates by pointing out that “We do not just see ‘A house’: We see a handsome house, an ugly house, or a pretentious

house” (p. 154). On the other hand, consumers cognitively elaborate on the stimulus (i.e., cognitive processing) by reflecting on the positive and negative consequences of a decision. Applying the dual-processing model to a privacy setting (see Figure 4.1; adapted from Bidler, 2019), consumers process a firm’s data request (i.e., a stimulus) by showing an affective reaction to it (positive or negative) and by performing a privacy-calculus evaluation, that is, weighing the benefits and risks of the disclosure situation (i.e., cognitive processing).

Figure 4.1. *Dual-Processing Model of Privacy-Related Decision-Making.*



While cognitive processing has received considerable attention from both research and practice, privacy research has only recently begun to focus on the importance of affect in privacy-related decision-making (e.g., Angst & Agarwal, 2009; Kehr et al., 2015; Keith et al., 2016). This is surprising as affective reactions can influence decisions in two ways: First, affective reactions can directly influence a decision-making process, i.e., consumers make decisions without (extensive) cognitive reflection, relying solely on their gut feeling (i.e., automatic positive or negative reactions) or certain heuristics (i.e., experience- or observation-based positive or negative reaction; Chaiken, 1987). According to prior research, this occurs because consumers prioritize low-effort affective processing over high-effort cognitive processing – especially when a stimulus elicits positive rather than negative affective reactions (Bohner et al., 1992; Kuykendall & Keating, 1990).

Second, affective reactions can indirectly influence a decision by adjusting perceptions of the specific stimulus (Loewenstein & Lerner, 2003). That is, when

consumers engage in cognitive processing, affective reactions bias the cognitive evaluations of the stimulus, which, for example, Hüttel et al. (2018) refer to as the “benefit-inflation” effect. The authors find that positive affective reactions to a stimulus lead to an overestimation of benefits (and an underestimation of risks), causing irrational (increased) consumer behavior. Similarly, in the context of consumer privacy, Kehr et al. (2015), for instance, show that affective reactions toward a stimulus adjust consumers’ perceived risks of disclosure.

In conclusion, findings from prior research illustrate that consumers are not able to eliminate the influence of affect in their decision-making processes (Darke et al., 2006; Steudner, 2021), which is why firms need to be aware of consumers’ affective reactions toward a stimulus such as a data request. After delineating the mechanisms behind consumer reactions towards a stimulus (e.g., a data request), the next section addresses the question of how affective reactions triggered by affective cues might influence consumers’ data disclosure expectations; these expectations, in turn, may have consequences for consumers’ long-term satisfaction with a decision.

4.2.2 The Confirmation-Disconfirmation Paradigm and a “Situation-Fit” Perspective on Affective Cues

In marketing research and practice, affective cues are primarily used to elicit positive (rather than negative) affective reactions that trigger consumer behavior desired by the firm. However, while consumer behavior such as data disclosure resulting from affect-driven decision-making is mostly favorable to the firm (e.g., consumer data helps the firm extend its competitive advantage), this behavior may not necessarily be perceived as beneficial by consumers. Particularly in situations, in which the outcomes of engaging in certain behaviors do not fit the expectations formed at the time of the decision, consumers may regret their data disclosure

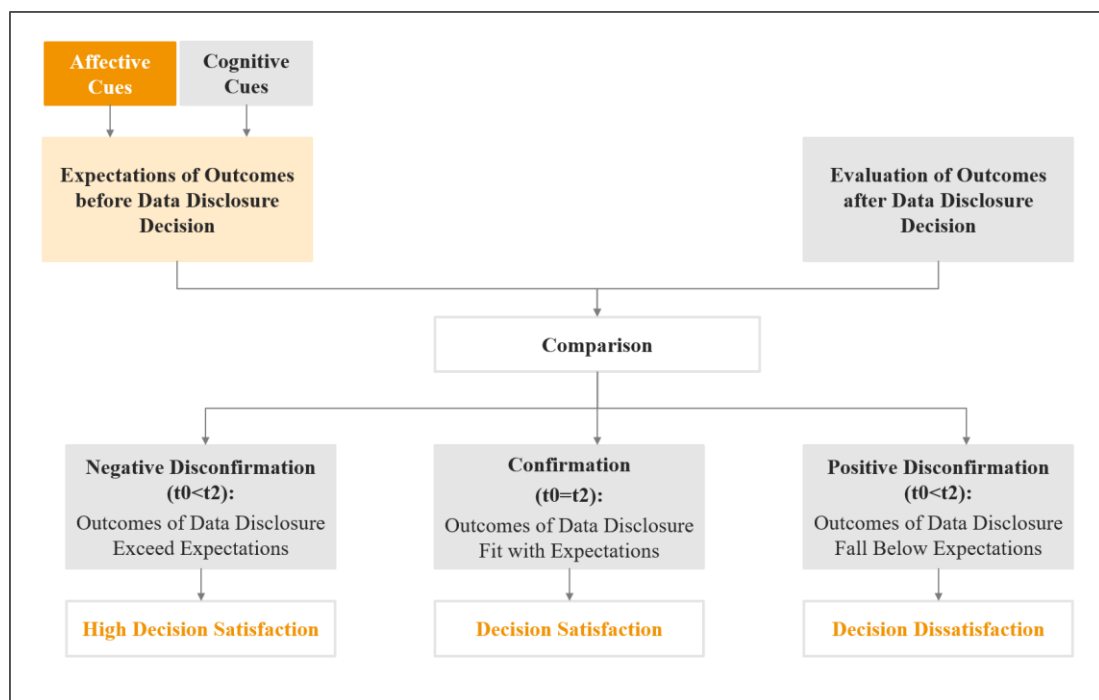
behaviors. Therefore, firms need to consider the potential long-term effects of consumers' (dis)satisfaction with a data disclosure decision for the benefit of the overall customer-firm relationship.

Applying the Confirmation-Disconfirmation (C/D) paradigm to explain consumers' evaluations of a privacy decision (Churchill & Surprenant, 1982; Oliver, 1980, 1993; Oliver & DeSarbo, 1988), the reason for a positive vs. negative ex-post evaluation of the decision may be the result of the comparison between the expected outcome of a decision (e.g., the expected benefit in exchange for engaging in a disclosure behavior) and actual outcomes after a decision (e.g., the benefit they actually receive from engaging in a data disclosure behavior; see Figure 4.2). The C/D paradigm explains that consumers are more likely to be satisfied with their initial decision to engage in a particular behavior such as data disclosure if the expected outcomes of a decision are met or even exceeded. In contrast, consumers feel dissatisfied if the expectations based on an evaluation of the outcomes are not met. In the context of data privacy, Krafft et al. (2021) support the C/D perspective by suggesting that consumers "often implicitly and automatically, evaluate whether or not the retailer is meeting these (...) expectations in their use of the data, which in turn affects beneficial (e.g., satisfaction) or detrimental (e.g., defection) consumer behaviors" (p. 5). This statement is in line with first empirical evidence from Swani and Milne (2022) on the importance of meeting privacy expectations for achieving satisfaction with a disclosure decision.

When comparing expectations with outcomes (e.g., benefits received in exchange for personal data), not only cognitive evaluations but also the affective processing of information experienced in the decision-making process plays an important role. Oliver (1993) explains that positive affect and negative affect in the decision process can significantly influence how consumers evaluate their decision

satisfaction; he further states that affective reactions, independent of cognitive evaluations, can influence decision evaluations. Thus, in the context of consumer privacy, affective reactions toward a data request (i.e., the evaluation basis for the decision to enter a data disclosure process) may shape consumers' outcome expectations of data disclosure and, consequently, influence whether or not they are satisfied with the decision after data disclosure or not. This assumption is consistent with prior research outside the privacy context by Mattila and Wirtz (2000), who show that affective reactions experienced in the pre-process stage (e.g., decision making) influence the consumers' post-process outcome evaluations (e.g., decision evaluation).

Figure 4.2. *Conceptual Model: C/D Paradigm Perspective and Consumer Privacy.*



To address the potential risk of dissatisfaction with a disclosure decision that has been based on or biased by affective reactions, this article proposes that there must be a fit between the affective cues employed to design a data disclosure request and the specific data disclosure situation. That is, firms should use affective cues that reflect or are related to the purpose of the data disclosure behavior. Otherwise,

consumers may feel tricked into a behavior that they regret when realizing that their decision was guided by an affective cue that had nothing to do with the actual situation; this dissatisfaction with a privacy outcome could then negatively impact the overall customer-firm relationship.

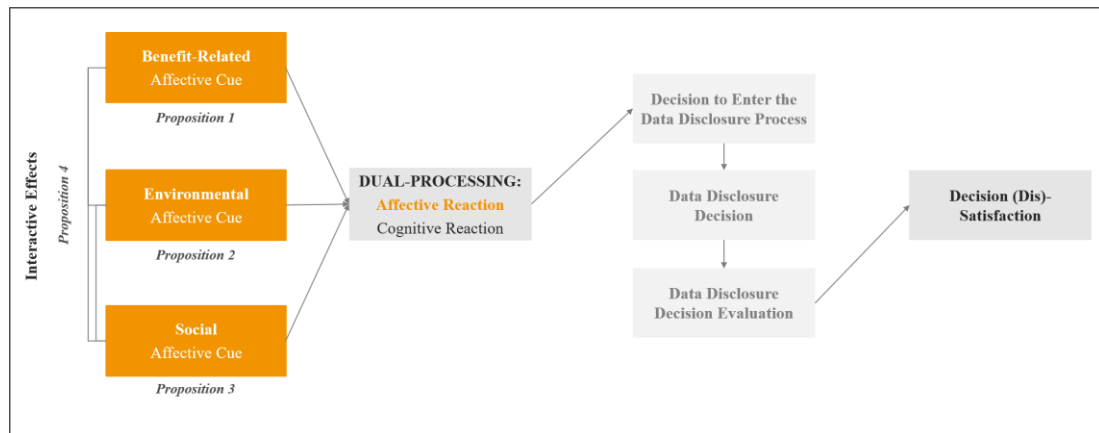
This article, however, does not claim that affective cues that do not fit a particular data disclosure situation will always result in poor decisions that consumers will feel dissatisfied with or regret; rather, it is to make firms aware of the opportunities they have to design data requests that elicit affective reactions that will have positive long-term effects, regardless of whether affect directly or indirectly influences the decision. Drawing on privacy research and real-world examples, the next section illustrates how companies can achieve a fit between affective cues and the specific data disclosure situation.

4.3 Understanding Affective Cues Against the Background of Decision Satisfaction and Situation-Fit

Based on examples from prior privacy literature (Table 4.1) and from practice, this article identifies three categories of affective cues with different properties, which can be used to shape consumer data disclosure expectations in order to help firms to design their data requests in a motivating way: Benefit-related, environmental, and social affective cues. Benefit-related affective cues can be considered essential factors because they are likely to influence expectations related to the outcome of data disclosure the most (i.e., in terms of what consumers receive in exchange for their personal data). Environmental and social affective cues can be considered rather supportive of consumers' privacy-related decision-making. This article provides examples for each category of affective cue and illustrates their effectiveness in influencing data disclosure behavior as reported by prior research.

Also, it discusses their potential effects on consumers’ long-term (dis)satisfaction with the data disclosure decision, providing propositions for each category of affective cues as well as for their interactive effects (see Figure 4.3).

Figure 4.3. *Affect-Triggering Factors in Data Requests: Effects on Entering Decisions and Disclosure Evaluation*¹⁰.



¹⁰ This article focuses on affective cues triggering affective reactions that influence consumers’ decision to enter a data disclosure process. As illustrated in the figure, although not the main focus, this article acknowledges that between the decision to enter a data disclosure and their perceived decision (dis)satisfaction, consumers perform the task of disclosing personal data (i.e., depending on the data disclosure form; Krafft et al., 2021) as well as the task of comparing whether their expectations align with the outcomes of data disclosure, which determines consumers’ (dis) satisfaction with a disclosure decision.

Table 4.1. Exemplary Research on Affective Cues in the Context of Privacy-Related Decision-Making.

Authors	Affective Cue	Investigating Long-term Consequences?	Findings Regarding Affect
Benefit-related Affective Cues			
Specific features of a stimulus that manifest the affective quality of the stimulus and relate to the benefit consumers receive in exchange for their personal data.			
Angst & Agrawal (2009)	Message framing	No	Positive information framing triggers affective reactions that lead to increased behavioral intentions to opt-in to electronic health records via (positive) post-manipulation attitudes.
Bidler et al. (2020)	Gamification	No	Affective relevance-illustrating game elements trigger affective processing of the disclosure purpose (i.e., hedonic engagement) and facilitate cognitive processing (i.e., meaningful engagement), leading to increased intentions to engage in data disclosure.
Trang et al. (2020)	Gamification	No	Gamified experiences (i.e., quizzes or social comparison) positively influence consumers' willingness to provide their social media account information to an app through cognitive absorption (i.e., affective processing). Cognitive absorption also moderates the positive effect of benefit perceptions on data disclosure.
Environmental* Affective Cues			
Specific features of a stimulus that manifest the affective quality of the stimulus and relate to the environment in which consumers make privacy-related decisions.			
Kehr et al. (2015)	Picture of a smiling car	No	Consumers' affective reactions toward a cute user interface (i.e., a smiling car) lead to an underestimation of the risks of information disclosure, which ultimately increases data disclosure intentions.
Li et al. (2011)	Website design	No	Consumers' initial emotions toward a firm's website and later-stage cognition-based perceived exchange fairness jointly influence privacy beliefs and, ultimately, disclosure intentions.
Li et al. (2017)	Website design	No	Consumers' cognitive appraisals formed during website interactions positively influence their liking of the respective website, which leads to increased disclosure intentions.
Najjar et al. (2021)	Website design	No	Consumers' intention to provide access to a mobile app is influenced by their satisfaction with the app. Positive affect influences satisfaction both directly and indirectly through increased perceived benefits (i.e., cognitive processing).
Wakefield (2013)	Website design	No	Positive affect fosters consumers' website trust and positively influences their privacy beliefs, which, in turn, motivate online information disclosure.

Social Affective Cues

Specific features of a stimulus that manifest the affective quality of the stimulus and relate to the social aspects involved in the privacy-related decision-making process.

Atiello et al.	Timing of data request	No	Consumers' warmth perceptions reduce their privacy concerns toward a data request, leading to a higher willingness to disclose personal information.
Joinson et al. (2007)	Personalized salutation, identifiability of consumers via personalized URL	No	Personalized salutations increase active non-disclosure behavior (i.e., selecting "I don't want to answer") but do not increase passive non-disclosure (i.e., not selecting any response option). In sensitive disclosure situations, an active non-disclosure option allows consumers to protect their privacy while ensuring survey quality.
Keith et al. (2016)	Indication of network size and app rating	No	The indication of the network size, representing an affective heuristic cue, adjusts consumers' risk-benefit evaluation of the disclosure situation (i.e., downloading a Location-based Service app). High network size and high post-disclosure peer rating lead to increased app downloads.

Notes: *As privacy seals and assurances fit the data disclosure situation (i.e., illustration of privacy protection in the specific data disclosure decision situation) and are either subject to industry-self-regulation or national law, they are not explicitly listed in this table. For a review of privacy seals and assurances representing affective environmental cues, see Gerlach et al. (2019).

4.3.1 Benefit-related Affective Cues

Affective reactions influence consumers' expectations of the benefits they will receive from firms in exchange for their personal data when engaging with a data request (i.e., the outcome of data disclosure). Prior research on affect toward benefits finds that consumers show affective reactions when an offering comes at no cost, leading to an overestimation of benefits and underestimation of risks (i.e., the "zero price" effect; Hüttel et al., 2018). This phenomenon can be reversed and adapted to a privacy context: Getting a benefit in exchange for data might (positively) bias consumers' benefit expectations as they receive a reward for something that comes at no cost for them (i.e., they usually do not have to pay for their own data) and for which they may not be used to get (much) compensation. Therefore, firms must generally be aware of a potential benefit overestimation due to affective reactions triggered by affective cues used in a data request when deciding what benefits they want to offer their customers in exchange for data.

In general, privacy research distinguishes between monetary and non-monetary benefits (Martin et al., 2020). Monetary benefits refer to compensations in the form of money or goods. From a situation-fit perspective these monetary offerings may not always be ideal for achieving long-term satisfaction with a disclosure situation; although they are effective in motivating data disclosure, monetary benefits are (usually) unrelated to the data disclosure situation (Dinev et al., 2015). Yet, consumers are likely to be rather satisfied with data disclosure decisions based on the monetary benefit if the amount of money or the goods they receive in exchange for their data fit with the value they attach to the specific data disclosed. In order to achieve consumer satisfaction with the outcome, firms must therefore consider different value expectations (i.e., depending on the data disclosure situation), as it has been shown, for example, that consumers expect higher monetary

compensation when the requested data is highly sensitive (Fast & Schnurr, 2020; Grossklags & Acquisti, 2007).

Another possibility to create affective reactions is to provide consumers with non-monetary benefits referring to compensations in the form of, for example, personalization or enjoyment. Prior research finds that non-monetary benefits, such as having fun in a gamified app when earning badges and points, can increase consumers' intention to disclose data (Trang & Weiger, 2021). Yet, evidence from practice outside the privacy context shows that such benefits can have potentially negative long-term consequences; for example, the online retailer Zappos was criticized for implementing game elements (i.e., affective cues) that did not fit the specific situation and the purpose of consumer behavior as rewards for customer loyalty. The misalignment of expectations (i.e., customers expected game elements to have a specific meaning beyond being fun) with the outcome of showing loyalty behaviors caused consumer dissatisfaction and led to a quick end of the program (eLearning Industry, 2017). Similarly, a study from Accenture Interactive (2018) finds that consumers want to understand the direct link between the requested data and the resulting personalization benefits (i.e., outcome of data disclosure) and that this is important for enabling trusting customer-firm relationships. Therefore, it is advisable for firms to explicitly choose both monetary and non-monetary benefits of data disclosure to fit the specific situation in order to increase long-term consumer satisfaction and, consequently, firm success.

To support the appreciation of data disclosure and the understanding of data disclosure benefits, firms can also use affective cues to facilitate cognitive benefit evaluations. Angst and Agrawal (2009) show that affective reactions elicited by positively framing the resulting benefits of data disclosure increase consumers' disclosure behaviors. Similarly, Bidler et al. (2020) find that triggering affect with

relevance-illustrating game elements not only helps consumers to better understand the purpose of data disclosure (i.e., cognitive processing) but also allows them to enjoy the disclosure experience (i.e., affective processing). While facilitating the cognitive processing of disclosure benefits is a promising approach, however, this may only lead to long-term consumer satisfaction if the benefit itself is aligned with the data disclosure situation. Based on the illustration of the importance of benefits in the context of data disclosure, the following proposition can be derived:

Proposition 1: If benefit-related affective cues fit the specific data disclosure situation, consumers are more likely to be satisfied with the disclosure decision when evaluating its outcomes after data disclosure.

4.3.2 Environmental Affective Cues

The environment (e.g., the website) in which firms present their data requests plays an important role in consumers' privacy-related decision-making (e.g., Li et al., 2011). A well-designed and user-friendly website is one way to reassure consumers and make the data disclosure situation affectively appealing. Generally, prior research shows that the overall design of a website can elicit both negative and positive affective reactions that (in)directly adjust consumers' disclosure intentions (Najjar et al., 2021; Wakefield, 2013). In their research, Kehr et al. (2015), for example, trigger positive affective reactions by integrating a smiling car (i.e., an environmental affective cue) into their data request, which increased consumers' intentions to disclose data. Similarly, many firms integrate cute or funny pictures and slogans into their data requests (e.g., pictures of real cookies) as well as use so-called "nudges" to foster data disclosure behaviors (Tacticx, 2021).

Such environmental affective cues support consumers' privacy-related decision-making. However, it is likely that consumers will not be satisfied with their decision if they realize that they have disclosed personal information in response to,

for example, a smiling car, a funny picture, or a privacy nudge that is unrelated to the specific situation and was intentionally designed to induce behavior that may not be in their best interest. General website design represents an environmental cue that does not necessarily has to fit the very specific data disclosure situation (i.e., firms design their websites for purposes beyond privacy) and is unlikely to induce strong perceptions of regret. Yet, firms can be thoughtful about how to avoid misleading affective responses and instead support consumers' privacy decisions and satisfaction, i.e., by using distinct affective environmental cues.

Li et al. (2017) provide the first evidence on the effectiveness of evoking privacy-related affective reactions with specific cues; they show that consumers' feeling of being in control over personal data increases website liking, which ultimately leads to increased disclosure intentions. To avoid misleading affective reactions toward a data request and to take advantage of affective reactions, firms may explicitly design and tailor affective cues to the disclosure situation; for example, the use of (affectively appealing) privacy assurances such as privacy seals represents a promising opportunity to foster long-term satisfaction. Such assurances are subject to either national regulation (e.g., General Data Protection Regulation) or industry self-regulation (e.g., TRUSTe) and, hence, need to fit the specific data disclosure situation. There are many examples from literature illustrating how to best use them (for a review see Gerlach et al., 2019); overall, firms should use environmental cues to support shaping consumer expectations that can be met.

Proposition 2: Environmental affective cues that are designed to fit a data disclosure situation support consumers' post-disclosure decision satisfaction.

4.3.3 Social Affective Cues

Consumers also show affective reactions toward social cues, such as the behavior of other people. With regard to other customers, research finds that the so-

called “herding effect” can be applied to the context of data disclosure. For instance, Keith et al. (2016) show that indicating the number of others who have downloaded a Location-based Service mobile application (i.e., disclose location-based data) increases the likelihood that other consumers will do so as well. In this case, the indicated network size serves as a social heuristic that consumers refer to when making decisions (e.g., in highly complex data disclosure situations). The authors also find that other people’s post-disclosure rating of the outcome of data disclosure (e.g., rating it with 1 to 5 stars representing affective cues) influences consumers’ decision-making. Thus, companies may include not only the number of customers who signed up for the service (i.e., disclosed personal information) in their data requests, but also whether the customers were satisfied with their decision. Both of these cues can be considered aligned with the data disclosure situation when they truthfully display other customers’ behaviors and evaluations.

Another social affective cue that influences consumers’ privacy-related decision-making is the indication of the person or firm requesting personal data. In this regard, Joinson et al. (2007) find that personalized data requests from a high-power person (e.g., a person with a high hierarchical job position) increase consumers’ data disclosure behavior. However, considering post-disclosure evaluations, it may be not advisable to create hierarchical distance based on such social cues that do not fit the disclosure situation (i.e., power positions have nothing to do with data disclosure) to motivate consumer behavior. Since the authors did not explicitly measure consumers’ affective reactions, it can only be assumed that consumers’ decisions are based on either negative (e.g., they might feel intimidated) or positive (i.e., they want to behave respectfully) affective reactions toward a data request by a high-power person. This would explain why the authors also find that

consumers are actually less likely to disclose sensitive personal data if they feel that they can be identified by their vis-à-vis who is not in a higher position of power.

Instead of creating hierarchical distance, firms may focus on creating closeness with their customers so that they trust them as data exchange partners. This is in line with Aiello et al. (2020), who investigate perceived warmth as an affective response to firm behavior that is aligned with data disclosure. They find that requesting data at a later stage in the customer retail journey (e.g., post-purchase) creates warmth, which reduces privacy concerns and subsequently leads to higher data disclosure behaviors. This can lead to positive post-disclosure evaluations as consumers are able to establish a (positively perceived) relationship with firms before deciding to share data with them. In conclusion, employing social affective cues that fit the data disclosure situation is likely to reassure consumers during and after the decision-making process, helping them to shape attainable expectations.

Proposition 3: Social affective cues that are designed to fit a data disclosure situation support consumers' post-disclosure decision satisfaction.

4.3.4 Interaction of Affective Cues

Both online and offline environments are inherently composed of multiple, different affective and cognitive cues, so consumers process not one but many cues when confronted with specific situations such as data disclosure (Moffett et al., 2021; Roggeveen et al., 2020). To date, research on affective reactions in the context of data disclosure has mainly focused on examining a single distinct affective cue and/or its interaction with one specific cognitive stimulus (e.g., Kehr et al., 2015; Li et al., 2011; Wakefield, 2013). Thus, privacy research still lacks deeper insights into the interaction of different affective cues, that is, an understanding of how benefit-related, environmental, and social cues can work in conjunction to influence privacy-related decision-making.

Investigating how multiple affective cues work together as well as how they interact with cognitive factors is becoming increasingly important, especially in the context of new, technology-driven data disclosure situations. Such situations confront consumers with complex information that is often difficult to process and understand (Quach et al., 2022). Preliminary research supports this assumption: For instance, Bidler et al. (2020) show that affective cues can enhance consumers' understanding of cognitive cues. Thus, it may be worthwhile for firms to design their data requests with multiple affective cues to support their customers' information processing. Applying the proposed situation-fit perspective of affective cues, the multiple cues used in data requests should fit the data disclosure situation and should be complementary rather than competing to jointly encourage data disclosure behaviors (see Figure 4.3). This approach will help to avoid creating expectations that cannot be met, leading to dissatisfaction with a data disclosure decision.

Proposition 4: Combining multiple affective cues (i.e., benefit-related, environmental, social) that fit a data disclosure situation enhances consumers' post-disclosure decision satisfaction.

4.4 Conclusion

Employing affective cues (i.e., benefit-related, environmental, and social) when designing data requests is a promising approach to supporting consumers' privacy-related decision-making. The categorization of affective cues illustrates their variety and how their properties can be used to design different aspects of the data request (e.g., affectively appealing environment). The proposed conceptual framework as well as the findings of this article emphasize that such cues should fit a data disclosure situation (i.e., reflect or be related to the purpose of the data disclosure behavior). When chosen accordingly, firms can meaningfully shape consumers' data disclosure expectations when entering a data disclosure process and,

subsequently, positively influence their post-data disclosure decision satisfaction. This general proposition is consistent with the C/D paradigm (Churchill & Surprenant, 1982; Oliver, 1993; Oliver & DeSarbo, 1988), which suggests that expectations (e.g., when entering a data disclosure process) form the basis for consumers' evaluation of whether or not they are satisfied with a decision such as data disclosure.

The author emphasizes that the situation-fit perspective introduced in this is particularly important with regard to benefit-related cues: An intentional design of data requests with benefit-related affective cues will help to avoid creating outcome expectations that cannot be met, so that consumers do not regret their decision to exchange their data. Further, this article illustrates that using environmental and social affective cues in data requests that fit a data disclosure situation further support consumers' privacy-related decision-making processes.

Overall, this article contributes to privacy research and practice by identifying three strategies for using affective cues to encourage consumers' disclosure behavior and foster their decision satisfaction. To the best of the author's knowledge, this article is the first to discuss the potential long-term effects of affect-driven decision-making on consumers' post-disclosure satisfaction and how to address them; as such, it adds to scarce privacy research explicitly investigating data disclosure expectations (Dinev et al., 2015; Krafft et al., 2021; Swani & Milne, 2022). By highlighting the importance of the fit between the affect cues and the data disclosure situation, it provides firms with hands-on recommendations for designing their data requests accordingly. Following the suggestions will help them to avoid the risk of tricking their customers into engaging in a disclosure behavior that they may be dissatisfied with when evaluating the outcomes of a data disclosure decision (e.g., because they overestimated the resulting benefits).

The propositions of this article encourage privacy research and practice to further (empirically) investigate how affective cues should be employed to promote consumers' privacy-related decision-making and decision satisfaction. This research is important because addressing affective reactions by intentionally designing affective cues may be a powerful tool for firms to provide consumers with an emotionally appealing experience, while may help to address their fatigue in making privacy decisions (Choi et al., 2018). Moreover, decisions based on well-designed affective cues have great potential for creating long-term data disclosure satisfaction in customer-firm interactions if consumers reflect positively on the data disclosure situation.

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5. General Discussion

In three essays, I sought to answer my overarching research question on how data requests can be designed to positively influence the consumer privacy journey (i.e., pre data disclosure, data disclosure, and post data disclosure phase). To answer this question, I focused on dual-processing models of decision-making to understand consumers' cognitive and affective processing of information when confronted with a decision to enter a data disclosure process (e.g., Epstein, 1994; Evans & Stanovich, 2013; Finucane et al., 2000). Essay 1 deals with a cognitive processing mechanism in the context of AI-based data disclosure processes: Consumers' perceived behavioral control over personal data. It offers a novel conceptualization and operationalization of data control's different nuances (i.e., data collection, submission, access, and use). Next, Essay 2 sheds light on how affective cues (i.e., relevance-illustrating game elements) and cognitive cues (i.e., relevance elements), when working in conjunction, increase consumers' intention to enter a data disclosure process. Finally, Essay 3 categorizes different types of affective cues (i.e., benefit-related, environmental, and social) and discusses, against the background of a situation-fit-perspective, how affective cues might influence consumers' post data disclosure decision evaluation. In the following, I will discuss my dissertation's theoretical and managerial contributions that go beyond the individual contributions and implications of each essay. I conclude with a brief outlook on the consumer privacy journey.

5.1 Theoretical Contributions

This dissertation offers three contributions to consumers' privacy-related decision-making and decision evaluation research in the context of the consumer privacy journey.

5.1.1 Introducing the First Step on the Consumer Privacy Journey

First, this dissertation focuses on customer reactions toward firms' data requests. According to the proposed consumer privacy journey, the evaluation of data requests represents the first step consumers take in privacy-related interactions with a firm, followed by the data disclosure process. The distinction between the pre data disclosure phase (i.e., first step of the consumer privacy journey) and the data disclosure phase (i.e., second step of the consumer privacy journey) proposed in my dissertation is critical for better understanding and addressing consumers' privacy-related decision-making: Complying with a data request and disclosing personal data are conceptually two different behaviors, though, prior research rarely differentiates between consumers' *intentions to enter a data disclosure process* and *intentions to disclose personal data*. Drawing this distinction allows me to explore how the initial decision to enter a data disclosure process can be influenced by the subsequent phases and vice versa. The findings of this dissertation show that data requests can be proactively designed and used to help consumers anticipate activities that occur immediately after their decision to enter a process as well as to evaluate potential consequences of data disclosure behaviors. Accordingly, this dissertation advances privacy research by emphasizing the need to focus on data requests as an important means for encouraging consumers' privacy-related decision-making and for meaningfully influencing the consumer privacy journey (e.g., Aiello et al., 2020; Schumann et al., 2014; Smith et al., 2011)

Specifically, Essay 1 demonstrates that when confronted with a data request, consumers can (mostly) distinguish between four different control activities related to the data flow stage and the data handling stage. In the context of AI-based (as opposed to non-automated) data disclosure processes, I show that anticipating flow control (i.e., anticipating the second phase of the consumer privacy journey) biases

consumers' perceptions of future data handling control activities as well as future benefits (i.e., evaluation base for third journey phase). Essay 2 also focuses on the first two phases of the consumer privacy journey. It provides insights into how integrating a preview of a data disclosure process into a data request helps consumers to better grasp the meaning of data disclosure. Finally, Essay 3 proposes to link privacy-related decisions based on the design of data requests as a means of shaping consumer expectations with consumers decision evaluations of the outcomes of data disclosure behaviors (Mattila & Wirtz, 2000; Oliver, 1980; Oliver & DeSarbo, 1988; Swani & Milne, 2022). I highlight that it is crucial to be aware of consumers' post disclosure evaluations when designing data requests as the evaluation of a particular situation can consequently influence the subsequent (data gathering) touchpoints of a firm and its partners. This informs research that discusses privacy as an important factor in the context of customer (retail) journeys (e.g., Cui et al., 2021; Martin & Palmatier, 2020).

5.1.2 Evaluating Consumers' Privacy-related Decision-Making Processes

Second, my dissertation contributes to an emerging stream of literature highlighting the role of dual-processing of information (e.g., Epstein, 1994; Evans & Stanovich, 2013; Finucane et al., 2000) in the context of consumers' privacy-related decision-making (e.g., Dinev et al., 2015; Gerlach et al., 2019; Kehr et al., 2015). While affective and cognitive processing mechanisms have already received considerable research attention (Bleier et al., 2020; Gerlach et al., 2019; Martin & Murphy, 2017; Smith et al., 2011), this dissertation demonstrates that there is still potential for research to better understand their peculiarities: Essay 1 focuses on improving our understanding of a specific cognitive processing mechanism, namely consumers' perceived behavioral control over personal data. It introduces a novel, multistage perspective on control over personal data and empirically shows that

consumers' perceived data control maps onto different activities (i.e., collection, submission, access, and use) of the customer–firm data exchange. This new, in-depth understanding of a core privacy construct complements privacy research, which has largely viewed control as a unidimensional construct (e.g., Brandimarte et al., 2013; Martin et al., 2017; Xu et al., 2012; Zhao et al., 2012).

Essay 2 empirically examines the interplay between cognitive and affective cues employed in data requests to motivate dual processing of privacy-related information. It finds that augmenting textual relevance arguments with relevance-illustrating game elements amplifies positive effects on consumers' willingness to comply with data disclosure requests. Furthermore, it contributes to research by highlighting that affective cues (e.g., game elements) need to be designed in a way that enables consumers to understand the meaning of data disclosure behaviors (Eisingerich et al., 2019).

Essay 3 takes up and expands this finding by introducing a situation-fit perspective on different categories of affective cues (i.e., benefit-related, environmental, and social). It conceptualizes that affective cues can only effectively motivate consumers' privacy-related decision-making *and* positively influence data disclosure decision satisfaction if they fit the specific data disclosure situation. In doing so, it extends research by considering the Confirmation-Disconfirmation paradigm in the context of consumer privacy (e.g., Bidler et al., 2020; Gerlach et al., 2019; Kehr et al., 2015; Li et al., 2011). Overall, the findings of my three independent essays answer to a call by Dinev et al. (2015) for research on the role of affective and cognitive processing in the privacy domain.

5.1.3 Exploring New Data Disclosure Touchpoints

Finally, I argue that there is a particular need to explore approaches for designing data requests (e.g., by effectively integrating affective and cognitive cues)

in the context of new data disclosure settings. This is consistent with recent research suggesting that new technological advancements challenge our current understanding of how consumers evaluate technology-enabled data disclosures and how these evaluations need to be addressed to increase consumer acceptance (Cui et al., 2021; Krafft et al., 2021; Quach et al., 2022; Steinhoff & Martin, 2022). The findings of Essays 1 and 2 contribute to this emerging stream of privacy research by demonstrating that technological advancements can both decrease and increase consumers' willingness to comply with a data request: Essay 1 focuses on AI-based data disclosure processes, which represent a new form of active data disclosure with characteristics of passive data disclosure (Krafft et al., 2021). It shows that the automation of data disclosure processes increases consumers' perceived data control risks. This provides AI research with new insights into an important obstacle to the adoption of AI-based products and services (Ameen et al., 2021; André et al., 2018; Schweitzer & van den Hende, 2016). In contrast to Essay 1 shedding light on consumer reactance to new technology-enabled touchpoints, Essay 2 highlights that technological advancements can also be used to achieve favorable consumer behavior. Results show that the integration of new tools, such as gamification, supports consumers' processing of data requests and helps them to make informed decisions when confronted with firms' data gathering efforts. Finally, the situation-fit perspective on affective cues proposed in Essay 3 also applies to contexts involving new data disclosure settings, particularly given that consumers are often highly skeptical when exposed to new technologies, such that it takes more to convince them to comply with data requests (de Bellis & Johar, 2020; Parasuraman & Colby, 2015; Quach et al., 2022).

5.2 Managerial Implications

Besides theoretical implications, my dissertation also offers important privacy-related insights for marketing managers.

5.2.1 Designing the First Step of the Consumer Privacy Journey

First, I advise firms to take a more holistic perspective on privacy-related decision-making by moving beyond an exclusive focus on consumers' data disclosure behaviors. As suggested by the proposed consumer privacy journey, decision-making (often) does not start with the actual data disclosure behavior (e.g., clicking the submit button) but with complying to enter a data disclosure process. This dissertation suggests that data requests should be considered the first, highly effective, and potentially powerful privacy-related touchpoint that firms need to focus on in order to increase their customers' willingness to provide them with personal data. To date, however, firms often use data requests in a generic, standardized way to comply with necessary regulatory requirements (i.e., to ask their customers for tracking consent), rather than exploiting their full potential: Data requests are versatile means and can be customized to meet the needs of both consumers and firms while, at the same time, complying with regulatory requirements. For instance, firms might display the data disclosure process in their data request to inform their customers about the next step and to depict the value they will derive from engaging in data disclosure behaviors (e.g., personalization benefits; Essays 1 and 2).

In addition, they can employ different (cognitive and affective) cues in their data requests to a) display their privacy assurances (e.g., transparency, control, benefit statements), b) create perceptions of social connection between customers, and c) design their websites to embed privacy information into appealing environments (Essay 3). Putting effort into thoughtfully improving privacy practices

likely also helps firms take advantage of new data disclosure touchpoints (e.g., those involving AI), making data requests a point of differentiation or even a source of competitive advantage.

5.2.2 Targeting Consumers' Cognitive and Affective Reactions

Picking up on the first managerial implication, the findings from my dissertation demonstrate that, in order to effectively motivate consumers' privacy-related decision-making, managers need to develop an understanding of both consumers' affective and cognitive processing of information. Essay 1 highlights that firms' assumptions about how their customers *ought* to perceive data disclosure situations may differ from their actual perceptions. Firms' understanding of consumer perceptions is crucial for the development of privacy-enhancing tools and mechanisms to precisely counteract negative reactions (e.g., due to a perceived loss of control over certain data activities). It is also important to carefully assess control risk perceptions across different data activities, as these perceptions may bias, for instance, benefit perceptions (Essay 1). This relates to Essay 3, as it suggests carefully eliciting affective reactions to shape consumers' initial decision to comply with a data request (in the pre data disclosure phase). Firms need to be aware that these affective reactions potentially bias consumers' outcome expectations, which may lead to dissatisfaction after data disclosure when the actual outcome does not fit with the expected outcome (in the post data disclosure phase).

Based on detailed knowledge of consumers' processing mechanisms, firms can take advantage of targeting them with cognitive and affective cues to effectively encourage consumers to comply with data requests. To this end, privacy research provides rich insights to managers on designing cognitive cues that target consumers' cognitive processing of data requests (e.g., Bleier et al., 2020; Martin & Murphy, 2017). This dissertation shows that cognitive cues, such as relevance arguments, can

prosperously work in conjunction with affective cues such as relevance-illustrating game elements (Essay 2). This ‘collaboration’ of cues helps consumers to process the information provided in a data request more easily, while anticipating the enjoyment they will experience when engaging in a data disclosure process. Thus, the use of different, carefully designed affective and cognitive cues is likely to help firms to persuade their customers to share their personal data. Finally, I provide firms with a categorization of different types of affective cues (i.e., benefit-related, social, and environmental; Essay 3) to illustrate the multiple ways, in which they can positively influence consumers’ privacy-related decision-making and decision satisfaction in the long term.

5.2.3 Adding Meaning to Data Disclosure

Finally, this dissertation encourages managers to design their data requests to convey the meaning of data disclosure behaviors in order to achieve mutually valuable customer relationships. That is, I advise firms to focus more on how disclosing data will benefit their customers, rather than focusing primarily on gathering as much data as possible to generate competitive advantage. This customer-centric approach to privacy means going beyond simply complying with regulatory requirements (e.g., GDPR guidelines for privacy notices on data handling) and demonstrating to consumers how firms’ data handling practices can create value for them. Truthfully highlighting the (positive) outcomes of data disclosure behaviors in data requests is particularly important in the context of new data-gathering technologies (e.g., as AI-based data disclosure processes). Essay 1 shows that consumers tend to be more skeptical about data handling practices as well as the benefits they receive in exchange for their data when they cannot fully control whether and how much data flows to a firm. In such cases, firms need to put more

effort into convincing consumers of the value they receive in exchange for their personal data to balance their control risks.

In addition, Essay 2 provides further empirical evidence for the pertinence of carefully designing data requests: In Study 3 of this essay, my co-authors and I compare consumer reactions when confronted with data requests featuring relevance-illustrating vs. hedonic game elements (i.e., arbitrarily chosen affective cues). Results highlight the importance of specifically tailoring game elements (i.e., affective cues) to convey the meaning of data disclosure (e.g., personalization benefits) in order to help consumers envision the future benefits of data disclosure. Finally, echoing Essay 2, adding meaning to data disclosure is particularly worthwhile for firms that seek to build and maintain long-term relationships with their customers. That is, based on findings from Essay 3, I recommend that firms should be considerate when motivating consumers' initial data entering decisions with affective cues to avoid that they feel tricked into data disclosure behaviors after reflecting on the decisions.

5.3 Outlook

Taken together, the findings of my dissertation make important contributions to research on consumers' privacy-related decision-making and decision evaluation. Its limitations provide promising avenues for further research on the consumer privacy journey.

5.3.1 Moving Beyond Single Data Disclosure Journeys

In my Essays, I have intentionally focused on single, distinct consumer privacy journeys as well as on discussing the interplay between data requests and either a data disclosure process (i.e., AI-based, gamified; Essays 1 and 2) or data disclosure evaluations (Essay 3). My findings suggest that it is worthwhile for both research and practice to explore the various facets of distinct data disclosure

situations. Yet, as mentioned in the introduction, prior privacy research implies that the customer (retail) journey involves multiple data disclosure touchpoints (e.g., Martin & Palmatier, 2020; Cui et al., 2022). Based on the consumer privacy journey perspective introduced in this dissertation, it may be a promising avenue for future research to investigate the interplay of different consumer privacy journeys across multiple customer-firm interactions. For instance, I recommend future research to investigate how a prior privacy experience with a firm (i.e., including the pre data disclosure, the data disclosure, and the post data disclosure phase) influences consumers' perceptions of a firm's subsequent (privacy-related) touchpoints along the customer (retail) journey. Investigating potential spill-over effect from one to another privacy-related touchpoint will help to provide a holistic understanding of consumers' privacy perceptions in certain interactions, which is particularly important given the emergence of new (technology-enabled) data disclosure settings and uses.

5.3.2 Calibrating Data Requests

Another important avenue for research is to empirically examine how different cues can be used jointly to meaningfully address consumers' privacy-related decision-making processes, as proposed in Essay 3. As in the case of investigating multiple data disclosures, privacy research does not account for data requests consisting of multiple cues but has focused on investigating one or two distinct cues at a time (e.g., Bidler et al., 2020; Gerlach et al., 2019; Kehr et al., 2015; Li et al., 2011). For instance, research could empirically examine how different combinations of affective and cognitive cues (e.g., benefit-related, environmental, social) influence consumers' appreciation of data requests. This could help to further enhance firms' ability to proactively shape consumer expectations. In doing so, future research could also consider different presentation formats (e.g.,

visual and verbal; Moffett et al., 2021). Making data requests more appealing by using a combination of cues could help to reengage consumers in data disclosure and address their privacy fatigue (Choi et al., 2018).

5.3.3 Conceptualizing and Measuring Privacy Perceptions

I also call for further research on more nuanced conceptualizations and operationalizations of privacy-related constructs. Essay 1 points out that, despite the existence of a large body of research on control over personal data, to date, privacy research still lacks an in-depth understanding of its conceptualization and operationalization. It also provides preliminary evidence that process benefits (i.e., reduced effort) do not equate to outcome benefits (i.e., personalization). As in the case of control, other privacy-related consumer perceptions may also be multistage and relate to different activities of the customer-firm data exchange. As such, privacy perceptions associated with the data flow stage are likely to differ from those perceived in the data handling stage, and might also relate to different facets of data disclosure (e.g., social and financial risks; Beke et al., 2021). I encourage research to continue to thoroughly define and measure privacy-related constructs when investigating consumers' reactions to established and new data disclosure settings.

5.4 References

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6. Conclusion

Consumers are increasingly restricting access to their data as firms expand their data proliferation efforts through new (technology-enabled) data collection capabilities. To counter this trend, firms need to better understand their customers' privacy needs in order to adequately address them. While prior research has mainly examined consumers' specific data disclosure behaviors (e.g., behavior of consenting to tracking or clicking the 'submit data' button), this dissertation advocates for a more nuanced view of privacy-related decision-making and introduces a consumer privacy journey perspective. In three essays, I focus on data requests, which represent the first steps of this privacy journey, and explore how they influence the subsequent steps of the journey (i.e., the data disclosure phase and the post data disclosure phase) and vice versa. Furthermore, I highlight the need to consider both affective and cognitive processing of information when confronting consumers with a data request in different (technology-enabled) data disclosure settings and processes, such as those involving gamification or AI. My findings contribute to privacy research by adding a new perspective on the multiple opportunities that data requests, when thoughtfully designed, present to firms and their customers. This dissertation also offers implications for managers on how to meaningfully motivate consumers' privacy-related decision-making for achieving long-term satisfaction with a data disclosure decision. Finally, my dissertation outlines fruitful avenues for future privacy research that are highly relevant for researchers, managers, and policymakers in today's modern data-driven economy.